Deleveraging Risk

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Abstract

Deleveraging risk is the risk attributable to investing in a security held by levered investors. When there is an aggregate negative shock to the availability of funding capital, securities with a greater presence of levered investors experience extreme return realizations as these investors unwind their positions. Using data on equity loans as a proxy for the degree of levered positions in a given stock, we find robust evidence of deleveraging risk. Stocks with a high degree of short selling experience large positive returns and a decrease in short selling around periods of funding capital scarcity.

JEL classification: G12; G14; G15

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I. Introduction

The extreme movements observed in asset prices and investment flows during the 2007–2008 financial crisis have renewed academic interest in the impact of liquidity shocks on financial markets. Gorton and Metrick (2012) analyse the events leading to the crisis and show how a run on repo markets led to a widespread increase in write-downs (i.e. "haircuts") applied to securities accepted as collateral, reducing the amount of capital available to investors. Heightened perceived risk can also lead to reduction in capital available to investors, inciting widespread selling of securities (i.e. fire sales) and creating a self-reinforcing cycle that widens mispricing. (See Shleifer and Vishny (2011) for a comprehensive survey.) Gromb and Vayanos (2002) discuss how large mispricing can generate forced deleveraging through lower collateral values. Brunnermeier and Sannikov (2014) model how financial intermediaries reduce their lending in downturns, limiting the amount of capital available to investors.[1] Together, these arguments suggest that investment strategies can face higher risk during periods of extreme market movements and capital scarcity. For example, Coval and Stafford (2007) show that unexpected withdrawals from mutual funds require the funds to suddenly close their long positions, leading to fire sales and temporarily reducing the prices of stocks held by these funds.

We name this source of uncertainty "deleveraging risk" and define it as the risk of losses due to a sudden and widespread reduction in investment positions in a given stock. This idea is central to traditional microstructure theoretical and empirical research on market impact. For example, Kyle (1985), Brennan and Subrahmanyam (1996) and Amihud (2002) emphasize how trading activity impacts prices and the extent of this relation is directly tied to the liquidity or depth of the market. Our notion of "deleveraging risk" builds on this theoretical link by noting that the presence of levered investors, sensitive to extreme market movements and reduced access to funding, are likely to have a significant

[1] For alternative channels by which asset prices can be affected by liquidity shocks and trading frictions, see Shleifer and Vishny (1992, 1997, 2011), Kyle and Xiong (2001), Brunnermeier and Pedersen (2009), Geanakoplos (2010), and Hanson and Sunderam (2014).

effect on security prices. During periods of market volatility and reduced access to funding capital, levered investors can be forced to reduce positions or may voluntarily decrease their risk exposure. This combination of forced and voluntary reductions in investment positions can lead to sudden reduction in long positions (e.g., Coval and Stafford (2007)). It can also force investors to cover their short positions (i.e., “fire purchases”). [2]

In this paper, we test the impact of sudden deleveraging on prices by examining stocks with a high intensity of short selling. Short selling is employed by sophisticated investors, who often combine it with leverage to magnify returns. Thus, it is reasonable to assume that a stock with high short-selling intensity is also likely to have a high proportion of short sellers using leverage when establishing their investment positions. The price impact of a decrease in capital available to investors should affect all levered long and short positions. Long levered positions are expected to exhibit “fire sales” (e.g., Coval and Stafford (2007) and Mitchell and Pulvino (2012)), and short levered ones to display “fire purchases” if investors must suddenly close their short positions. We expect that the most levered long positions exhibit extremely negative returns during periods of funding withdrawals. However, because we cannot observe which stocks are held by levered long investors, we cannot test for negative returns from sales of long positions in these stocks, especially at daily frequency. Stocks with low short selling are not necessarily those with a higher proportion of long, levered investors.

One might expect highly shorted stocks to generate significant profits during aggregate stock market decreases. Our paper shows, surprisingly, this is not the case. We find there is a relative price increase for the most shorted portfolio of stocks during periods of market shocks and reductions in funding. Like past research, we identify a negative relationship between short selling and future stock returns using several measures of short selling (e.g., Aitken, Frino, McCorry, and Swan (1998), Dechow, Hutton,

[2] “Short squeeze” is a term used when short sellers are pressured to quickly cover their positions in an individual stock due to firm-specific shocks. These rare stock-specific events mostly occur in small cap stocks. We use the term “fire purchases” to denote events when a systematic shock (e.g., reductions in funding capital) leads short sellers to cover their positions across different stocks, akin to an aggregate “short squeeze.”

Meulbroek, and Sloan (2001), Asquith, Patak, and Ritter (2005), Boehmer, Jones, and Zhang (2008), and Cohen, Diether, Malloy (2007)). However, this negative average relationship is interrupted by periods in which stocks with the highest levels of short selling experience very strong *positive* returns. This relationship relates to events such as those around the Lehman Brothers bankruptcy in Sep. 2008, and to changes in variables such as the VIX index and the credit default swap index for the U.S. banking sector, both associated with economy-wide reductions in funding. In summary, we show that fire sales and purchases also happen on the short-leg of portfolios (i.e., stocks with the highest proportion of short selling). When levered short sellers face a shock that leads to a sudden reduction of their positions, stocks with the highest levels of levered investors can even exhibit positive returns.

Given the lack of data on stock holdings at a frequency higher than quarterly, equity lending markets provide a valuable data source to identify stocks with more shorting by levered investors.[3] By using daily equity lending, we can analyse how prices move after deleveraging shocks at a much higher frequency than previous papers.[4] Our primary measure of short selling is the ratio of the value of securities on loan to the total market capitalization of that security on a given day, $ONLOAN$. We also employ three other measures of short-selling intensity: (i) the ratio of the number of securities on loan to the number of shares that were available to be loaned, $UTILIZATION$; (ii) the ratio of the number of shares sold short to the total number of shares traded that day from the New York Stock Exchange (NYSE)'s SuperDOT platform, $SHORT\_VOLUME$; and (iii) the monthly ratio of the number of shares shorted to the number of shares outstanding, $SHORT\_INTEREST$.[5]

[3] Long positions must be reported by institutional investors through 13F fillings. Short positions do not have to be reported to the SEC.
[4] The vast majority of equity loans are made for the purpose of short selling (Saffi & Sigurdsson (2011)).
[5] While $SHORT\_INTEREST$ is only available at a monthly frequency, it covers a much larger period, ranging from Jan. 1990 to Aug. 2013. We use the monthly volume summary files from the NYSE to compute $SHORT\_VOLUME$ and compute this measure for a smaller sample of U.S. equity securities that are traded on the SuperDOT platform for the Jul. 2006 to Jun. 2012 period.

We run time series regressions of the $LOW - HIGH$ portfolio's daily returns based on stocks sorted by short selling activity as a function of the standard Fama-French factors (MKT, SMB, and HML), the momentum factor, and a daily liquidity factor based on Corwin and Schultz (2012)'s bid-ask spread estimator. Additionally, we include specific measures designed to capture the market-wide effects of illiquidity as reflected by (i) indicator variables for large negative market returns on the previous day, (ii) indicator variables to capture the periods associated with the so-called Quant crisis of Aug. 2007 (Khandani and Lo (2011)) and the Lehman Brothers bankruptcy in Sep. 2008, (iii) changes in the VIX volatility index, (iv) changes in the TED spread, (v) changes in convertible bond spreads relative to their fair price (Mitchell and Pulvino (2012)), (vi) changes in the $NOISE$ funding illiquidity measure proposed by Hu, Pan, and Wang (2013), and (vii) changes in the 5-year credit default swap index of the U.S. banking sector ($CDS5y$). We also use principal component analysis to extract a common factor for liquidity as an additional variable, obtaining similar conclusions.

Overall, we find evidence consistent with the hypothesis that a dislocation in the ability of levered investors to maintain their positions coincides with positive returns for stocks that have a greater concentration of short sellers. For example, during the Lehman Brothers crisis, we estimate the daily equal-weighted abnormal returns to a portfolio that sells highly shorted stocks and buys the least-shorted ones is about −241 basis points, in contrast with 10 basis points during normal trading days.

We also examine the persistence of returns for highly shorted securities and the changes in quantities of securities sold short following a reduction in funding. We see a pattern of higher security prices across several of our funding measures for up to 80 trading days beyond the initial shock. This suggests that the effect is not immediately reversed. We also document a significant reduction in equity loan quantities following periods of deleveraging for most of our arbitrage capital measures, supporting our findings that a reduction in leveraged short positions drives the stock return results.

Together, these results suggest that the unwillingness or inability of levered investors to maintain their position sizes most likely explains the occasional strong positive relation between short selling and future returns and that this effect continues for some time after the initial reduction in funding. To our knowledge, we are the first researchers to investigate the impact of funding shocks on short sellers, adding novel evidence to the literature on these types of shocks.

The paper proceeds as follows. Section II develops our hypothesis. Section III describes our data sources. Section IV explains our research design. Section V shows the empirical results and considers further alternatives for deleveraging patterns. Section VI concludes.

II. Hypothesis Development

Our primary hypothesis is that the abnormal returns of highly shorted stocks are less negative and can even become positive following periods of funding illiquidity. Because short sellers set up their strategies with widespread usage of leverage, stocks with the highest levels of short selling face higher levels of deleveraging risk when funding is suddenly withdrawn. When liquidity evaporates and short positions have to be covered, securities with a greater presence of levered investors experience a significant shock as these investors unwind their positions, voluntarily or not. These movements push the prices of highly shorted stocks upward, affecting them relatively more than those stocks with low levels of short selling.

There are at least three nonmutually exclusive explanations for why levered investors may be unable to maintain levered positions during periods of capital scarcity. First, portfolio managers may voluntarily reduce the leverage of their portfolios to maintain a desired ex ante risk level in response to economy-wide liquidity shocks (Kyle and Xiong (2001), Xiong (2001), Bollerslev, Hood, Huss and Pedersen (2016), and Moreira and Muir (2016)). If market volatility increases, investors might choose to employ less leverage in their portfolio.

Second, investment funds' clients may withdraw capital during periods of economy-wide liquidity shocks (Shleifer and Vishny (1997) and Coval and Stafford (2007)). Such shocks tend to happen when there is a general demand for collateral. This does not force a portfolio manager to reduce a portfolio's leverage, but it will cause a reduction in position size if she does not simultaneously increase leverage of the remaining investors' equity.

Third, prime brokers may reduce the amount of leverage they are willing to extend to portfolio managers in response to economy-wide liquidity shocks. Hence stocks with a greater presence of levered investors should experience more extreme returns as these investors decide, or are forced, to react to a reduction in funding by unwinding their positions (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Brunnermeier and Sannikov (2014)).

Regardless of the exact reason why investors choose to reduce their investment positions during periods of capital scarcity, all of the potential explanations are consistent with our hypothesis that a sudden attempt to reduce position size can lead to aggregate short covering. If the demand by levered short sellers trying to buy shares to cover their positions is offset by levered long investors trying to exit their positions in a given stock following deleveraging events, we would not expect any pricing effects. However, if the aggregate pressure to close short positions is strong enough to have a price impact, we would expect to observe returns even being positive following liquidity shocks for stocks with the highest ex ante short selling intensity.

Our ideal research design would require identification of the portfolio weights of all portfolios that use leverage for both long and short positions. It is not possible to obtain this information from publicly available data. Instead, we use various measures of short selling to proxy for latent leverage. Thus we assume that short sellers use leverage in their portfolios and securities with a high level of short selling activity have higher presence of levered investors. These are reasonable assumptions since this is how a typical levered investment strategy works. The typical long/short equity strategy employed by a market-neutral hedge fund starts with an initial investment of \$X. The investor will then create a portfolio with weights such that the final portfolio has a desired ex ante risk level. To achieve the target level of risk, the fund manager will typically employ leverage via a prime brokerage relationship. The fund manager will use prime brokerage financing to "borrow" $\$L^{S}\cdot X$ worth of securities and purchase $\$L^{L}\cdot X$ worth of securities. The $\$L^S \cdot X$ worth of securities that are sold short are captured by the short selling data. However, we cannot uniquely identify the $\$L^L \cdot X$ worth of securities that are purchased by the levered long investor.

To support our assumption that short selling reflects portfolio leverage, we examine aggregate leverage measures and how they correlate with measures of short selling. Note that we must use aggregate measures because security-level leverage data for individual investors is unavailable. We examine the relation between three different measures of leverage and short selling at the aggregate level. First, we use leverage data computed by Morgan Stanley for fundamental long-short equity hedge-fund clients of the firm's prime brokerage arm. The sample includes U.S. long-short accounts with at least \$50 million in equity and is rebalanced every six to 12 months to keep it representative of historical accounts. Each fund is equally weighted in aggregate metric. Correlations between monthly aggregate measures of leverage and short interest are strongly positive and statistically significant. The correlation between changes in long-short hedge funds' leverage and changes in the market-wide mean fraction of shares lent out from Jul. 2006 through Jun. 2013 equals 0.24. If stocks with high short selling activity are also associated with a large presence of levered investors, we would expect an even higher correlation than that of the average stock. If we use the top 95th percentile to compute the correlation, it is statistically significant and equal to 0.34, consistent with our hypothesis. Second, we compute the correlation between the monthly leverage of equity hedge funds estimate by Ang, Gorovyy, and van Inwegen (2011) and the monthly difference of short interest for stocks in the most- and least-shorted quintiles from Dec. 2004 to Sep. 2009, which equals 0.25. Third, using NYSE's member organizations gross (net) margin account debt leverage, we find that the correlation with short interest for stocks in the most-shorted quintile is 0.73 (0.54). Given these significant correlations in aggregate short selling and aggregate portfolio leverage, our assumption that short sellers are likely to be levered investors seems reasonable.

While we aim to assess the impact of deleveraging risk on equity securities, there is related literature exploring the impact of leverage constraints and deleveraging risk on asset pricing. For example, Garleanu and Pedersen (2011) show that binding margin constraints can create price gaps between securities with identical cash flows but different margin requirements. Likewise, Brunnermeier and Pedersen (2009) show that funding liquidity can have significant effects on asset prices. In particular, it can reinforce margin requirements, leading to large and sudden moves in security prices. More generally, Duffie (2010) and Mitchell and Pulvino (2012) show that jumps in price gaps, and hence large "tail" returns, are evident across a variety of arbitrage strategies including (i) CDS-corporate bond arbitrage, (ii) convertible debt arbitrage, (iii) merger arbitrage, (iv) closed-end fund arbitrage, (v) index arbitrage, and (vi) "on the run" vs. "off the run" Treasury auction arbitrage. The impact of deleveraging risk, as reflected by the reduction in hedge fund capital deployed to these risky levered strategies, is consistent with our analysis. We can show a far broader impact of deleveraging risk into the full cross section of equity securities, beyond traditional arbitrage strategies.

Deleveraging risk is also related to the notion of crowded trades (e.g., Greenwood and Thesmar (2011) and Hanson and Sunderam (2014)). Our aim is to extend this literature by focusing on cross sectional variation in security sensitivity to the tail risk attributable to the presence of levered investors. The trigger that creates the tail risk we document is not measured from correlation in infrequently measured portfolio holdings (as by Greenwood and Thesmar (2011)) or from aggregate measures of arbitrage capital (as by Hanson and Sunderam (2014)). Rather, we focus directly on security-specific measures of equity lending, which allow us to investigate our hypothesis using stock-level daily data.

Our analysis focuses directly on the existence of levered investors as a potential source of tail risk. We do not focus on a given anomalous return strategy such as momentum and instead focus on a portfolio that replicates the positions of levered short sellers. Under our maintained assumption that short selling relates directly to the presence of levered investors, we can identify cross sectional differences in the presence of levered invested capital. Thus it enables us to focus on the *direct* asset pricing implications of levered positions on a particular stock following liquidity shocks. Our analysis therefore has the potential to explain tail risk across a variety of strategies, not just momentum (e.g., Daniel and Moskowitz (2014), Daniel, Jagannathan, and Kim (2012), Barroso and Santa-Clara (2016)).

III. Data

A Equity Lending and Short Sales Data

We obtain our measures of short selling from three sources: Markit (previously Data Explorers), NYSE, and Compustat. Our daily measures of $ONLOAN$ (defined as the value of the shares lent out divided by the stock's market capitalization) and $UTILIZATION$ (defined as the value of the shares lent out divided by the value of shares available to lend) use data sourced from Markit, which collects data on equity loans and lendable amounts from major participants in the securities lending industry. According to Markit, the data cover more than 85% of the transactions in the industry. We have $ONLOAN$ and $UTILIZATION$ available for the period from Jul. 2006 to May 2013. As of Dec. 31, 2010, there are more than $3.16 trillion dollars' worth of stocks available to borrow and $253 billion on loan from 702,826 reported transactions. We can compute an additional measure of short selling, $SHORT\_VOLUME$, from intra-day short selling for NYSE securities that trade electronically on the SuperDOT platform, where the vast majority of NYSE's trading volume is executed (see Boehmer et al. (2008)). Using the volume summary files, we compute the fraction of daily stock volume involving a short seller, which is available for the period from Jul. 2006 to Jun. 2012 for all stocks traded through the platform.

We also use $SHORT\_INTEREST$ from Compustat, defined as the monthly short interest reported by U.S. stock exchanges as a fraction of market capitalization, which is available from Jan. 1990 to Aug. 2013 and allows us to investigate whether our effects remain significant on a larger sample. More detailed definitions of each variable used in the paper are provided in the appendix.

It is important to clarify the timing of short sales and the measurement of equity lending variables. Following a short sale on day *t*, the short seller must settle the trade and deliver the securities sold by

t+3. Equity loans are settled on the same day that a loan is initiated, so a short seller can borrow the shares at t+3 for delivery to the buyer and minimize his borrowing costs (Geczy, Musto, and Reed (2002)). Thus $ONLOAN$ observed on day *t* captures short sales that were initiated at $t-3$. For regressions with returns as the dependent variable, we use $ONLOAN$ observed at time *t*, since it is what is known to investors at time *t*, similar to the approach used by Ringgenberg (2011). Whenever the dependent variable is the quantity of shares shorted, we use $ONLOAN$ measured at t+3 as a proxy for short selling taking place on day *t*.

B Funding Availability

We employ several variables related to funding availability and costs of financial intermediaries. From Datastream, we download the VIX index to proxy for changes in volatility and use the TED spread as a proxy for the funding costs faced by leveraged investors. Furthermore, we obtain data on the convertible bond spread relative to its fair price ($HAIRCUT$) used by Mitchell and Pulvino (2012), and the funding illiquidity measure ($NOISE$) estimated by Hu et al. (2013) based on deviations of U.S Treasury yields from a fitted term structure. Finally, we use Datastream's 5-year credit default swap index of the U.S. Banking Sector ($CDS5Y$) as a proxy for counterparty risk (Arora, Gandhi, and Longstaff (2012) and Gorton and Metrick (2012)).

C Other Data Sources

We merge the equity-lending and short-selling data with information from CRSP, Compustat, and Thomson Reuters. From the Center for Research in Security Prices (CRSP), we exclude closed-end funds, American Depositary Receipts (ADRs), and real estate investment trusts (REITs) and collect data on daily returns, market capitalization, stock turnover, and bid-ask spreads for common stocks. These data are further merged with Compustat for accounting variables needed to compute book-to-market

(B/P). We obtain institutional ownership data from the Thomson Reuters CDA/Spectrum database, with quarterly holdings data reported by investment companies and money managers with assets over $100 million under management. From Wharton Research Data Services (WRDS), we download the Fama-French and momentum factors' daily portfolio returns (i.e. MKT, SMB, HML, and UMD). We also construct a daily liquidity factor ($SPREAD$) based on Corwin and Schultz (2012)'s bid-ask spread estimators to capture the sensitivity of short selling-based portfolios to liquidity risk. Stocks are ranked on the previous month's average of daily bid-ask spreads, and the returns of the $SPREAD$ risk factor are defined as the daily difference between the top and bottom quintiles.[6]

D Commonality in Funding Availability

Each of our funding measures captures a different dimension of funding liquidity. Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) exploit the commonality in stock liquidity measures. A natural extension of our tests is to use principal component analysis to extract an underlying common factor for the funding liquidity variables.

In Panel A of Table 1, we display results for the five principal components using 1,611 days when all variables are jointly available. We follow the approach of Mancini, Ranaldo, and Wrampelmeyer (2013) and standardize all variables. The first principal component ($PC1$) can explain almost 70% of the total variance, being the only factor with an eigenvalue above one. These results indicate that the other common factors are negligible. Panel B of Table 1 contains the factor loadings on each of the five funding liquidity variables for $PC1$, and one can see that the weightings are evenly distributed across the five measures, with each contributing relatively the same. In Panel C of Table 1, we use these loadings to

[6] In unreported analysis, we have replicated all of our empirical analyses after removing securities with a share price below $5. Our findings and inferences are unaffected by this filter, suggesting our results are not attributable to a liquidity effect in small, illiquid securities.

extract the common factor and compute its correlation with the five funding liquidity variables. As expected, $PC1$ is positively correlated with all variables, with the correlation being greater than 0.6 in all cases. $PC1$ has correlations above 0.9 with the VIX, $HAIRCUT$, and $NOISE$ measures.

IV. Research Design

Our empirical approach is straightforward. For each day (*t*), we assign stocks using various short selling measures to one of five quintiles and compute average returns on the *following* day (i.e., *t+1*) for stocks in the bottom (LOW) and top ($HIGH$) quintiles. We then examine the returns of the strategy that buys stocks in the bottom quintile and short stocks in the top quintile to test our hypothesis; i.e., we track the returns of the $LOW - HIGH$ portfolio. While this strategy, in line with the literature, exhibits significant *positive* average returns (i.e., securities with the highest level of short selling have lower future returns than those with the lowest levels of short selling), our focus is on whether the portfolio also shows significant *negative* returns at times of capital scarcity. In particular, we examine variables designed to capture the following adverse effects on levered investments: (i) significant increases in market-wide volatility and counterparty risk, (ii) sudden increases in arbitrageurs' funding costs, and (iii) sudden drops in market wide returns. We also test whether the $LOW - HIGH$ portfolio faced extremely negative returns during the Quant crisis and during the Lehman Brothers' bankruptcy. While each crisis event had very different triggers, both created a need for levered investors to reduce their positions. The Quant crisis corresponds with the period described by Khandani and Lo (2011), i.e., Aug. 6 to Aug. 8, 2007. The Lehman bankruptcy is defined as the period from Sep. 16 to Sep. 18, 2008.[7]

[7] This period is before the ban on short selling of financial stocks imposed by the SEC on Friday, Sep. 19, 2008 (http://www.sec.gov/news/press/2008/2008-211.htm)

Our primary empirical specification is as follows:

$$(1)\quad LOW-HIGH_t = \alpha + \beta_{MKT} \cdot MKT_t + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{MOM} \cdot MOM_t + \beta_{SPREAD} \cdot SPR_t$$

$$+ \beta_{Ret(MKT)<2.5\sigma} \cdot D_{Ret(MKT)<2.5\sigma,t-1} + \beta_{QUANT} \cdot D_{QUANT,t} + \beta_{LEHMAN} \cdot D_{LEHMAN,t}$$

$$+ \beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta HAIRCUT} \cdot \Delta HAIRCUT_{t-1}$$

$$+\beta_{\Delta NOISE} \cdot \Delta NOISE_{t-1} + \beta_{\Delta CDS5y} \cdot \Delta CDS5y_{t-1} + \beta_{\Delta PC1} \cdot \Delta PC1_{t-1} + \varepsilon_t.$$

$LOW-HIGH$ is the daily (equal- or value-weighted) return from taking long (short) positions in securities in the bottom (top) quintile of a particular short-selling measure (i.e. LOW minus $HIGH$ portfolio). As control variables, we use the standard Fama-French factors (MKT, SMB, and HML), the momentum factor (MOM), and a daily liquidity factor ($SPREAD$) based on Corwin and Schultz (2012) bid-ask estimator. We also add several measures to capture the market-wide effects of funding illiquidity. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable for large negative market returns, being equal to 1 if the aggregate market return on the *previous* day is more than 2.5 standard deviations below the average and 0 otherwise. The standard deviation is estimated from a GARCH(1,1) model estimated on a rolling 252-day basis. D_{QUANT} is an indicator variable equal to 1 for trading days between Aug. 6, 2007, and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 for trading days between Sep. 16, 2008, and Sep. 18, 2008, and 0 otherwise. ΔVIX_{t-1} is the change in the VIX volatility index from day $t-2$ to day $t-1$. ΔTED_{t-1} is the change in the TED Spread from day $t-2$ to day $t-1$. $\Delta HAIRCUT_{t-1}$ is the change in the convertible bond spread measure by Mitchell and Pulvino (2012). $\Delta NOISE_{t-1}$ is the change in the funding illiquidity measure based on Treasury yields by Hu et al. (2013). $\Delta CDS5y_{t-1}$ is the change in Datastream's 5-year credit swap index from day $t-2$ to day $t-1$. And $\Delta PC1_{t-1}$ is the change in the funding liquidity common factor using principal component analysis. We use changes in funding liquidity variables rather than their levels to capture unexpected increases, similar to the approach of Acharya and Pedersen (2005).

The timing of our various liquidity variables is important, with all being measured at the close of the previous trading day. We choose this timing convention because we want to focus on the consequence of shocks to funding on the performance of a portfolio exposed to deleveraging risk. Our short-selling-mimicking portfolio is based on information available on day $t-1$. We assess the return performance of this portfolio on day *t* and, in particular, focus on the consequence of shocks to funding immediately before that return performance.[8] We also run cross sectional regressions using a panel of daily stock returns, allowing interactions of the various short selling and firm controls with the liquidity measures. Our inferences are robust to this alternative research design choice.

V. Empirical Results

A Descriptive Statistics

In Table 2, we present descriptive statistics. The average (median) firm in our sample has a market capitalization of $4.2 billion ($0.5 billion) with 56% (62%) of shares being held by institutional investors. On average, 18.9% of a firm's market capitalization is available for lending, with 4.2% being on loan. Some stocks are heavily borrowed, while others are not borrowed at all. $ONLOAN$ is as high as 27% in our sample. The average (median) $SHORT\_VOLUME$ equals 21% (21.1%), suggesting that short sales of NYSE stocks on the SuperDOT platform correspond to about one-fifth of trading volume. Furthermore, the average value of $UTILIZATION$ is 18.2%, implying that almost one-fifth of shares available to be loaned are actually on loan. The average (median) annualized lending fee is 101 (12) basis points, showing that, on average, it is very cheap to borrow shares. But there are clearly exceptions; the cost of borrowing an equity security can be as high as 2,275 basis points on an annualized basis. The

[8] In unreported tests, we have recomputed our various liquidity measures using contemporaneous data from day *t*, and our inferences are unaffected by this alternative timing choice.

remainder of Table 1 reports information on control variables and our various liquidity measures in both levels and changes.

In Figure 2, we show time-series and cross sectional variation in $ONLOAN$ for U.S. stocks during our sample period. For each day, we plot the mean, median, 20th, 80th, and 95th percentiles of $ONLOAN$. The lower tail of $ONLOAN$ is relatively stable through time, but, in contrast, the right tail of $ONLOAN$ exhibits considerably more volatility. We have super-imposed shaded areas corresponding to the Quant and Lehman Brothers crises, and it is clear that these events correspond to a significant change in terms of security borrowing and hence leverage, a necessary condition for our empirical predictions. Following the Lehman Brothers' bankruptcy, in particular, there is a noticeable decrease in $ONLOAN$, a consequence of aggregate deleveraging and the imposition of short selling constraints by the SEC.

B Relation between $ONLOAN$ and Future Stock Returns

In Figure 3, we plot the cumulative returns to an investment strategy that replicates exposure to short selling intensity. Each day, we sort securities into five groups based on the breakpoints of $ONLOAN$ from the previous day. We then compute equal- and value-weighted returns for the lowest and highest $ONLOAN$ quintiles, and the difference in these quintile portfolio returns (lowest minus highest) is the hedge return from exposure to $ONLOAN$. The top panel of Figure 3 shows a strong positive return to this strategy, consistent with an extensive previous literature examining short interest (e.g., Asquith et al. 2005): stocks with higher (lower) short selling activity are associated with lower (higher) future stock returns.

Our main focus, however, is on the occasional large negative returns to this strategy that happen around certain dates. Two such events occurred during the Quant crisis in Aug. 2007 and the Lehman Brothers' bankruptcy in Oct. 2008, with both exhibiting days with large negative returns in the $LOW - HIGH$ portfolio. The greater volatility in the returns to the $LOW - HIGH$ portfolio after these events is readily apparent in the top panel of Figure 3. To help isolate this effect, in the bottom panel of Figure 3, we plot the conditional daily volatility of the $LOW - HIGH$ portfolios from a GARCH(1,1) model. It is very clear that the Quant and Lehman crises are both strongly associated with sharp increases in the return volatility of the $LOW - HIGH$ portfolio, with daily volatility almost tripling relative to pre-event levels.

To isolate the determinants of these return realizations of a strategy mimicking levered investors, we decompose the $LOW - HIGH$ portfolio between its long and short sides and examine the days with the largest negative return $LOW - HIGH$ portfolio realizations. Figure 4 reports these details for the 15 (13) days in which standardized returns for the equal- (value-) weighted $LOW - HIGH$ portfolio are more than 2.5 standard deviations below the mean. The left (right) panel in Figure 4 reports raw returns for equal (value) weighted $LOW - HIGH$ portfolios. Our prior is that the negative realizations of the $ONLOAN$ hedge portfolio will be attributable to liquidity shocks affecting the ability of the levered marginal investor to maintain their portfolio exposures. Thus we expect the *short* leg of the $LOW - HIGH$ portfolio to experience large positive returns, and we do not expect much movement for the long leg of the $LOW - HIGH$ portfolio. While the analysis in Figure 4 does not condition on explicit measures of funding — it is based only on days with extreme negative returns for the $LOW - HIGH$ portfolio — it shows that the extreme negative return days observed by the long-short strategy are *all* driven by large positive returns of the high $ONLOAN$ quintile. This is consistent with the idea that the presence of levered investors causes an additional source of risk: the removal of leverage in the financial system can cause large and sudden changes in security prices, primarily for those securities exposed to such leverage. For example, on Sep. 17, 2008, two days after Lehman Brothers filed for bankruptcy and the day that the U.S. Treasury announced the AIG bailout, the return of the high $ONLOAN$ stock portfolio equals +8.41%. If a hedge fund was shorting stocks in the top $ONLOAN$ quintile and had a 3:1 leverage ratio (i.e., $1 of equity for every $3 of asset value), it would have lost 25% on a single day.

In Figure 5, we examine abnormal returns around the Quant crisis (top panel) and the Lehman Brothers' bankruptcy (bottom panel) for high $ONLOAN$ and low $ONLOAN$ stock portfolios using Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) characteristic-adjusted returns. Consistent with the analysis in Figure 4, the high $ONLOAN$ quintile drives extreme positive returns in both cases. Furthermore, the returns we plot in Figure 5 are "abnormal" with respect to sensitivity to the standard Fama-French factors plus momentum. To the extent that there are correlated positions across levered investors due to commonality among trading strategies with the standard risk factors used in the literature, the patterns we document in Figure 5 might be understated (e.g., Daniel et al. (2012) and Daniel and Moskowitz (2014)).

C Calendar-time Analysis with $ONLOAN$ Variable to Sort Stocks

Table 3 reports our primary regression analysis where we report nested versions of estimating equation (1) using equal-weighted portfolios based on $ONLOAN$ measure as the sorting variable. For ease of interpretation, we include predicted signs for each explanatory variable. There is a reliably positive intercept, suggesting the $LOW - HIGH\ ONLOAN$ strategy generates about 10 basis points of abnormal returns per day on an equal-weighted basis. Using geometric averages, this corresponds to annualized returns of about 26.7%. We find a very strong negative loading on MKT and SMB and very high R^2s for these regressions, similar to Jones and Lamont (2002). Likewise, Desai, Ramesh, Thiagarajan (2002) find that portfolios with exposure to higher levels of short selling have high positive exposures to market returns and the SMB factor. Given that our portfolio is a $LOW - HIGH$ portfolio based on $ONLOAN$, our negative exposure to MKT and SMB is consistent with prior research from earlier periods. We also find that the $LOW - HIGH$ portfolio is positively exposed to MOM. (Desai et. al. (2002) show a reliably negative exposure to MOM for their long highly shorted security portfolios.) The $SPREAD$ factor to control for liquidity (Corwin and Schultz (2012)) also has the expected positive sign, suggesting that a fraction of the returns to short selling strategies reflect compensation for general liquidity risk and ruling out the abnormal performance of short selling strategies is due to exposure to liquidity risk.

Our primary interest, however, is the behaviour of $LOW - HIGH$ portfolio returns during periods associated with deleveraging. Columns (2) to (8) examine the measures related to funding illiquidity. For all variables, our prior is a negative relation with respect to the daily returns of the $LOW - HIGH\ ONLOAN$ portfolio in the following day. Consistent with the evidence in Figure 5, we see very strong evidence of large negative returns to the $LOW - HIGH\ ONLOAN$ portfolio on the days of the Quant and Lehman crises. For example, in column (2) of Table 3, the β_{QUANT} regression coefficient is -1.579. This means that, while the $LOW - HIGH\ ONLOAN$ portfolio averages about 11 basis points of returns per day, conditional on days of illiquidity crises, the returns are -147 basis points. This is a strikingly large asymmetry relative to the average return profile and is consistent with deleveraging risk having a very strong economically and statistically significant impact on security prices. Likewise, the β_{LEHMAN} regression coefficient is -2.511, even more negative effect than found for the Quant crisis. Whilst the economic magnitude of these indicator variables is very large, it is useful to remember that they only occur for a small number of days (three days for each episode) due to the extreme nature of these events. Turning to the continuous measures of funding liquidity in columns (3) to (7), we see that all measures are negatively associated with the returns of the $LOW - HIGH\ ONLOAN$ portfolio. Finally, we compute the lagged first-difference of the principal component estimated in Table 1 and include it as an additional explanatory variable in column (8) with similar results. Overall, the evidence in Table 3 provides consistent evidence that the returns to the $LOW - HIGH\ ONLOAN$ portfolio are negative during periods of funding illiquidity.

D.1 Calendar-time Analysis with Alternative Short-selling Intensity Measures

Our primary analysis focused on the equal-weighted returns of one measure of short selling: $ONLOAN$. There are alternative measures to be extracted from financial markets, including $ONLOAN$, $UTILIZATION$ (measurable daily for the period of Jul. 2006 through to May 2013 from Markit), $SHORT\_VOLUME$ (measurable daily for the period of Jul. 2006 through to Jun. 2012 from the NYSE Volume Summary Files), and $SHORT\_INTEREST$ (measurable monthly for the period of Jan. 1990 through to Aug. 2013 from Compustat).

These measures capture different aspects of short selling, and it is important to ensure that the relation we document is robust to them. Our ideal construct is to know the extent of leverage employed by the marginal investor for every stock on every day. We have used the ratio of the number of shares on loan to the total number of shares outstanding as a proxy for this construct. To the extent that a firm's shares are closely held, not easy to locate for borrowing, or both, $ONLOAN$ may classify the firm as having a low value of relative short selling (and hence levered investor activity), even though, at the margin, there might be a greater presence of levered investors for such securities. To address this issue, we also compute $UTILIZATION$, defined as the ratio of the number of shares on loan relative to the number of shares that are available to borrow.

Column (1) of Table 4 reports our regression results based on equation (1) using equal-weighted returns of $ONLOAN$ stock portfolios on a specification that includes all funding illiquidity measures. We can observe that the coefficients for ΔTED and $\Delta Haircut$ are no longer significant , being subsumed by $\Delta NOISE$ and $\Delta CDS5y$. To facilitate comparison with other short-selling intensity measures, column (2) reports the same results shown in column (8) of Table 3 using $\Delta PC1$. In columns (3)-(4), we change our measure of short-selling intensity and use $UTILIZATION$ to construct $LOW - HIGH$ portfolio returns. Consistent with earlier results, we document a reliably positive intercept, suggesting the $LOW - HIGH$ $UTILIZATION$ strategy generates about 10 basis points of abnormal returns per day on an equal-weighted basis. Likewise, we continue to see strong negative loadings on MKT and SMB, a strong positive loading on MOM but no statistically significant relationship to HML and $SPREAD$. Of more direct interest, however, is the continued strong negative relation between the returns for the $LOW - HIGH\ UTILIZATION$ strategy and our various measures of funding liquidity. For example, the regression coefficients β_{QUANT} and β_{LEHMAN} are both below -2, suggesting that the $LOW - HIGH\ UTILIZATION$ strategy generates losses of more than 200 basis points on days of significant deleveraging.

Both $ONLOAN$ and $UTILIZATION$ are stock-based measures of short selling (i.e., they are based on end of day positions). In recent years, there has been a significant shift in the trading patterns of investors. In particular, there has been an increased prevalence of so called high-frequency trading, and some researchers argue that the majority of trading on the primary stock exchanges is attributable to investors with holding periods of less than a week (e.g., Haldane (2010)). We use data from the NYSE Volume Summary files to compute $SHORT\_VOLUME$, defined as the ratio between the number of shares that were sold short on a given day and the total number of shares traded on the SuperDOT platform for each stock. Column (5)-(6) in Table 4 reports our results using $SHORT\_VOLUME$ to construct $LOW - HIGH$ portfolio returns. Consistent with earlier results, we find a positive intercept, with the equal-weighted $LOW - HIGH\ SHORT\_VOLUME$ strategy generating abnormal returns of 7 basis points per day. Likewise, we continue to see negative loadings on MKT and SMB and a positive loading on MOM, but now there are much lower R^2s for these time-series regressions. The loadings we document resemble those reported by Boehmer et al. (2008). We also continue to find a negative relation between the returns for the $LOW - HIGH\ SHORT\_VOLUME$ strategy and the Quant and Lehman crises. For the other funding liquidity variables, results are somewhat weaker. The coefficient on ΔVIX and ΔTED are not statistically significant, but this might be caused by multicollinearity among funding liquidity variables. Using the funding liquidity factor ($\Delta PC1$) extracted from the principal component analysis can overcome this problem and allows us to examine common variation in our funding liquidity measures. In all cases, we find that the funding liquidity factor has a negative correlation with the returns of the $LOW - HIGH$ portfolio.

D.2 Calendar-time Analysis with Alternative Portfolio Weighting Schemes

The calendar-time analysis presented in Tables 3 and 4 are based on equal-weighting stock returns to construct portfolios. Asparouhova, Bessembinder, and Kalcheva (2013) show that these weights may bias inference due to microstructure effects, which can make prices deviate from fundamental values. This spurious noise can be an issue in our tests, particularly because we use daily returns in the analysis. Thus, in Table 5 we present results using the two main weighting schemes recommended by Asparouhova et al. (2013), which are shown in simulations to have minimal bias due to noisy prices. The first one, VW, weighs stocks based on their market capitalization in the previous day. The second one, RW, computes weights based on stocks' gross returns (i.e. one plus their return) in the previous day. For the sake of brevity, we only report results using the funding illiquidity principal component ($\Delta PC1$) and display additional results in Table IA.1 of the Internet Appendix (available at www.jfqa.org).

For all columns we can observe that the β_{QUANT} and β_{LEHMAN} coefficients are significant regardless of the weighting-scheme employed. The funding illiquidity's principal component ($\Delta PC1$) coefficient is significant in most cases. In columns (1)-(2) we find that an increase in funding illiquidity ($\Delta PC1$) is associated with a decrease in returns in the following period for the $ONLOAN$-based portfolios regardless of the weighting-scheme employed. Results in columns (3)-(6) are only significant for the return-weighted (RW) portfolios. Overall, our main results are robust to controls for noisy prices due to microstructure effects.

D.3 Calendar-time Analysis with Short Interest

Our final supplemental measure of short selling is the traditional measure of $SHORT\_INTEREST$, defined as the number of shares that the exchange lists as being held short relative to the number of shares outstanding. This measure has the advantage of a much longer time series, although not at daily frequency. We take $SHORT\_INTEREST$ starting in Jan. 1990 for all U.S. securities in Compustat and use values at the end of the previous month to sort stocks, rebalancing the portfolios once a month.

Table 6 reports our regression results using $SHORT\_INTEREST$ to construct equal-weighted $LOW - HIGH$ portfolio returns. Consistent with prior research, there is a very significant positive intercept, and again we find that the $LOW - HIGH$ $SHORT\_INTEREST$ portfolio returns have strong negative loadings on MKT, SMB, and HML and a positive loading on MOM and $SPREAD$. Over this longer period, we see that large negative aggregate market returns are associated with a significant reversal in the $LOW - HIGH$ $SHORT\_INTEREST$ portfolio returns. As before, we see a strong negative relation between the returns of the strategy and our measures of funding availability for a much longer period for all variables apart from $\Delta NOISE$ in column (6).[9] In the Internet Appendix, we obtain similar results to those in Table 5 when computing value-weighted and return-weighted portfolio returns based on $SHORT\_INTEREST$ as a measure of short-selling intensity. In Table IA.2, we find that results for value-weighted portfolios are somewhat weaker when using similar specifications to those shown for equal-weighted portfolios in Table 6.[10]

E Cumulative Stock Returns

So far, we have not discussed whether the impact of reductions in funding on levered securities is transitory or permanent. To address this issue, we extend the window over which we measure excess

[9] The sample size is smaller when we include $\Delta HAIRCUT$ as this variable is only available from October 2005 onward.

[10] Results found for the specification tested in columns (5) and (6) of Table IA.1 are also similar.

returns. This allows us to assess whether the positive returns found for stocks with high short selling intensity immediately following illiquidity periods reverses over subsequent periods or whether they persist.

We re-estimate equation (1) using cumulative returns for up to 80 trading days. The dependent variable is the cumulative returns of the $LOW - HIGH\ ONLOAN$ equal-weighted portfolios from t to *t+j*, where *j=[1, 2, 3, 4, 5, 20, 60, 80]* trading days. The risk factors (MKT, SMB, HML, MOM, and $SPREAD$) are also compounded over the $[t, t+j]$ window, while the illiquidity variables are held fixed at the values measured at the end of day *t−1*, so the cumulative return patterns are attributable to any reversals based on those fixed characteristics. Equation (2) summarizes our specification:

$$(2)\ LOW - HIGH_{t,t+j} = \alpha + \beta_{MKT} \cdot MKT_{t,t+j} + \beta_{SMB} \cdot SMB_{t,t+j} + \beta_{HML} \cdot HML_{t,t+j} + \beta_{MOM} \cdot MOM_{t,t+j}$$
$$+\beta_{SPREAD} \cdot SPR_{t,t+j} + \beta_{Ret(MKT)<2.5\sigma} \cdot D_{Ret(MKT)<2.5\sigma,t-1} + \beta_{QUANT} \cdot D_{QUANT,t}$$
$$+\beta_{LEHMAN} \cdot D_{LEHMAN,t} + \beta_{\Delta VIX} \cdot \Delta VIX_{t-1} + \beta_{\Delta TED} \cdot \Delta TED_{t-1} + \beta_{\Delta HAIRCUT} \cdot \Delta HAIRCUT_{t-1}$$
$$+\beta_{\Delta NOISE} \cdot \Delta NOISE_{t-1} + \beta_{\Delta NOISE} \cdot \beta_{\Delta CDS5y} \cdot \Delta CDS5y_{t-1} + \beta_{\Delta PC1} \cdot \Delta PC1_{t-1} + \varepsilon_t.$$

In Table 7, we report the estimates found for the liquidity variables, with columns (1a), (1b) and (1c) showing results for the regression with the extreme negative market return and crisis-event variables ($D_{Ret(MKT)<-2.5\sigma}$, D_{QUANT}, D_{LEHMAN}), column (2) for ΔVIX, (3) for ΔTED, (4) for $\Delta HAIRCUT$, (5) for $\Delta NOISE$, (6) for $\Delta CDS5y$, and (7) for $\Delta PC1$. Standard errors are estimated using heteroskedasticity and autocorrelation-consistent (HAC) covariance matrices to correct for the autocorrelation in cumulative returns, and the lag-order is chosen using the selection algorithm proposed by Newey and West (1994).

For *j=1*, reported coefficients are identical to those found for next-day returns (i.e. *t*+1) of the $LOW - HIGH\ ONLOAN$ portfolios in of Table 3. As we examine larger cumulative return windows, we find that all measures of liquidity shocks are statistically significant for the first week of trading following (i.e., *j=5*) and also for *j=20* trading days (i.e., a month) except for the estimate for D_{QUANT}. Even after three months, most estimates are still significant. It is only when we examine the cumulative returns after four months (i.e., j=80) that most estimates, apart from D_{QUANT} and D_{LEHMAN}, are no longer significant. Tables IA.3 and IA.4 in the Internet Appendix shows that we obtain similar results if portfolios are constructed using value-weighted and return-weighted returns.

In summary, the cumulative returns for the $LOW - HIGH$ portfolio are consistently lower following illiquidity shocks, and these results persist for up to three months. Collectively, these results suggest that securities with the highest level of short selling experience *positive* returns around periods of funding illiquidity.

F Changes in Equity Loan Quantities

A further test of our hypothesis that investors cover their positions after funding shocks is to investigate changes in equity lending *quantities*. To the extent that the levered marginal investor closes (i.e., covers) his short positions at the time of a funding shock, it should result in lower levels of short selling. Given the results in Table 7, if the price effects still persist up to 80 trading days after an economy-wide liquidity shock, we should also observe a decrease in equity loans not only on the day after the shocks but also for the ensuing period.

For this analysis, we pool all stocks in our daily data, creating a panel of nearly 4.7 million daily stock return observations. We employ panel regressions similar to the specification in equation (2) but now use changes in $ONLOAN$ from t+3 to t+3+j ($\Delta ONLOAN_{i,t+3+j}$) as our dependent variable, including year-month fixed effects and computing standard errors clustered at the firm level. Note that $\Delta ONLOAN_{i,t+3}$ is the cumulative change in $ONLOAN$ between t+2 and t+3, which is a proxy for changes in short sale quantities between t and $t-1$ due to the mechanics of equity loans' settlement dates described in section III.A.

Our regression specification is as follows:

(3) $\Delta ONLOAN_{i,t+3+j} = \alpha_t + \beta^T X_{i,t-1} + \gamma^T X_{i,t-1} \otimes Z_{i,t-1} + \varepsilon_{i,t}$.

β^T is a vector of regression coefficients and X is a vector of firm characteristics that includes $BETA$, $SIZE$, B/P, $RET6M$, $RETURN_{t-1}$, $ILLIQ$, and $SPREAD$. We also include separate indicator variables if the stock belongs, respectively, to the highest or lowest quintiles of $ONLOAN_{i,t-1}$ as part of X. This is meant to capture the effects of changes in equity loan quantities for the most and least shorted stocks, allowing for asymmetric effects between them. Z is a vector of funding variables that includes, respectively, $D_{Ret(MKT)<-2.5\sigma}$, D_{QUANT}, D_{LEHMAN}, ΔVIX, ΔTED, $\Delta HAIRCUT$, $\Delta NOISE$, $\Delta CDS5y$, and $\Delta PC1$. γ^T is a vector of regression coefficients capturing all interactions between all firm characteristics and the funding availability measures, including main effects for variables in Z, subjecting our hypothesis to a high hurdle rate. We report our results in Table 8 and only report interactions between $ONLOAN$ and the various funding availability measures for the sake of brevity. All variables are defined in the appendix.

Our prior is that the removal of funding (including increased margin requirements, recall of securities lent out, client redemptions, etc.) will cause levered investors to close out short positions. This covering pressure will, in part, generate the positive return relation documented in previous tables. For example, following the Lehman bankruptcy, $ONLOAN$ quantities decrease even faster for stocks with the highest levels of $ONLOAN$ (i.e. row (1c) of Panel A), relative to the mean reversion regularly observed in normal times.[11] To provide an economic interpretation for the −0.193 value for the $ONLOAN*D_{LEHMAN}$ regression coefficient shown in column (1c), we can compare it to the (unreported) −0.03 regression coefficient for the high $ONLOAN$ dummy variable. It implies that the speed of mean reversion in short selling is much larger during the Lehman bankruptcy crisis relative to the baseline effect. The only variable in Table 8 that does not have the expected sign is $\Delta CDS5y$. The coefficients on $\Delta CDS5y$ are positive rather than negative, with equity loan quantities increasing following increases in the $CDS5y$

[11] The unreported coefficients for the level of $ONLOAN$ (i.e., the "main" effect) are all negative and increasing in the window length j used to measure cumulative changes in $ONLOAN$ quantities for all the different sets of explanatory variables used. These coefficients capture the mean reversion commonly observed for short selling intensity.

index at time t and raising the issue of whether $CDS5y$ is a relevant measure of funding liquidity. After a month (i.e., t+20) the coefficients are still negative and significant, apart from $\Delta NOISE$ and $\Delta CDS5y$. At t+80, $\Delta NOISE$ and $\Delta CDS5y$ are no longer significant, consistent with the patterns observed in Table 7. When we consider changes of the principal component factor ($\Delta PC1$) in row (7), estimates are negative and statistically significant for all window sizes evaluated.

Together, the results in Tables 7 and 8 suggest that the large negative returns we document for the $LOW - HIGH\ ONLOAN$ portfolios are partially attributable to the withdrawal of funding by the marginal levered investor, consistent with our hypothesis that "fire purchases" reflect liquidity shocks.

Another possibility is that negative shocks to lending supply could be driving the reduction in $ONLOAN$ that we document in Table 8. We have examined separately the change in lendable supply using the same approach and find a muted response. In Table 2, we see that the majority of stocks in the U.S. are unconstrained, with the average $UTILIZATION$ implying that only 18% of available supply is lent out. This is more consistent with a shock to shorting demand rather than shorting supply and supports the findings of Cohen et al. (2007).

G Possible Causes of Deleveraging

Our empirical analysis thus far has established that securities with high levels of short selling exhibit positive returns after periods when capital is harder to obtain. There are multiple potential reasons for this observed relation. Deleveraging can be caused by a combination of voluntary actions of portfolio managers as well as involuntary actions of investors and financial intermediaries. Portfolio managers may seek to target an ex ante risk level for their fund. In response to economy-wide funding liquidity shocks or increases in risk-aversion, they may voluntarily reduce the risk of their portfolios, primarily through a decrease in leverage. This would cause selling pressure on long positions and buying pressure on short positions. Second, clients of the portfolio manager may take direct actions in response to economy-wide liquidity shocks and withdraw capital from risky portfolios. Such clients can be external (i.e., ultimate owners), internal ones (i.e., fund managers may have internal capital allocated from a parent entity or seed capital provider), or both, and their actions would be forced upon the portfolio manager, who would then need to return capital. This would make arbitrageurs reduce their notional positions, unless they simultaneously increased their leverage, again leading to selling pressure on long positions and buying pressure on short ones. Similarly, the prime broker who provides the leverage for the portfolio manager may take direct action in response to economy-wide liquidity shocks. Such actions could include explicitly reducing the leverage extended to the portfolio manager, increasing the collateral that must be held against portfolio positions, or both. All of these outcomes would lead to selling pressure on long positions and buying pressure on short ones if portfolio managers cannot put up the required increase in margins.

To help illuminate the voluntary deleveraging and ex ante risk targeting, in Figure 1 we analyse the daily hedge-fund gross leverage and the common component of funding liquidity, finding a noticeable negative association between these two variables. These changes in gross leverage may be due to (i) targeting constant portfolio volatility (i.e., gross leverage will decline when volatility rises, as is typical during periods of funding illiquidity) and (ii) systematic internal drawdown controls that curb gross leverage during times of funding illiquidity. We spoke informally with several prime brokers, and the consensus of these discussions was (i) hedge fund leverage has indeed fallen from the pre-2008 period (as reported by Ang et al. (2011)), (ii) during the Quant period, there were several examples of significant deleveraging (i.e., some funds were running at up to 15x gross leverage and relatively small, but correlated, price movements precipitated sudden deleveraging), and (iii) during the Lehman period, known arbitrage relationships broke down (e.g., convertible bond arbitrage and basis trades), which precipitated significant deleveraging for the funds with large exposures to these strategies. Hence voluntary deleveraging is likely to be a significant reason for the deleveraging risk we document.

To analyse client withdrawals from risky portfolios, we examine the time-series correlation between aggregate hedge-fund flows and leverage. We obtain aggregate hedge-fund leverage data from Ang et al. (2011), which comes from a fund-of-funds provider and tracks leverage over the period of Dec. 2004 to Oct. 2009. The overlapping period with our sample is 42 months of data. We also compute aggregate equity hedge-fund flow data from HFR and Lipper-TASS. We use the equity market-neutral style from HFR and Lipper-TASS as well as the equity long/short style from Lipper-TASS. We cannot find any robust correlations between aggregate hedge-fund leverage and flow data. We examined contemporaneous, leading, and lagging correlations. This lack of result is perhaps not surprising, as many hedge funds have in place so-called gates, and the redemption process often requires formal applications that occur on a set cycle. This suggests that external client redemptions are unlikely to completely explain the observed deleveraging we document. We do not have access to internal capital allocated to equity hedge funds, so we cannot directly comment on internal client redemptions as a cause of deleveraging risk. However, based on anecdotal discussions with hedge fund managers, especially those operating on platforms such as D. E. Shaw, Millennium, Citadel, and SAC, there are clear procedures in place to mitigate losses in periods of market stress (e.g., stop-loss rules). Thus it is likely that involuntary internal capital withdrawal only partly explains the deleveraging risk that we document. This is also consistent with the results of Ben-David, Franzoni, and Moussawi (2012).

Finally, we discussed forced reduction in positions with several prime brokers. The common assessment was that closing of short positions due to recalls is rare and stock-specific and applies mainly to small cap stocks. Forced deleveraging by prime brokers is also unusual. Hence forced deleveraging is unlikely to explain our results. This suggests that a voluntary reduction in leverage by portfolio managers is the most likely explanation for our observed deleveraging risk.

VI. Conclusion

We explore the impact of deleveraging events on the cross section of equity returns. We find evidence that deleveraging risk — the risk of losses due to a sudden and widespread reduction in stocks held by levered investors — affects equity returns. Using various measures of short selling from multiple sources for a large sample of U.S. securities, we find that stocks with high short selling activity experience occasional and very large positive returns during periods associated with reduced capital availability. Our assumption, validated by aggregate data and institutional features of how market-neutral equity funds operate, is that short sellers employ leverage as part of their investment strategy. We can therefore identify the effects of liquidity shocks to levered positions by tracking the actions of participants in the equity lending market.

The equity lending market is a natural source of data to quantify the presence of levered investors and the potential effect on stock prices since it aggregates the positions of short sellers across securities. Consistent with prior research, we find that, on average, there is a negative relation between measures of short selling and future stock returns across a variety of measures. However, extending the literature, we document evidence of occasional very large positive returns to short selling. We further find that these episodes of positive returns are associated with (i) discrete liquidity events, such as the Quant crisis of Aug. 2007 and the Lehman Brothers bankruptcy in Sep. 2008, and (ii) reductions in capital availability as reflected in a variety of measures such changes in TED spread, (iii) changes in convertible bond spreads relative to their fair price (Mitchell and Pulvino (2012)), and (iv) changes in the $NOISE$ measure used by Hu et al. (2013).

The return effects following funding shocks are economically significant and persist for up to 80 trading days for all the measures employed. The effect on equity lending quantities is also persistent, and we find evidence of significantly lower quantities on loan for up to 80 trading days after deleveraging shocks. Together, the continuation of positive returns for securities with high levels of short selling after periods of reductions in funding and the reduced quantities of short selling suggest that the withdrawal of funding for the marginal levered investor is the likely explanation for the effects we document.

These results may help regulators and investors understand the risks associated with short selling and the impact of the use of leverage on their portfolios around times of reduced capital availability.

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Appendix: Variable Definitions

$SUPPLY$	Daily total number of shares available to borrow from Markit divided by shares outstanding.
$ONLOAN$	Daily total number of shares on loan from Markit divided by total number of shares outstanding.
$SHORT\_INTEREST$	Shares Held Short as of Settlement Date (SHORTINTADJ), obtained from Compustat's Monthly Updates – Supplemental Short Interest File in WRDS, divided by total number of shares outstanding.
$SHORT\_VOLUME$	Daily number of shares marked as short sales on NYSE divided by total volume.
$UTILIZATION$	Daily number of shares on loan from Markit divided by the total number of shares available to be lent from Markit.
$VW\ Fee$	Daily loan-weighted average fee (bps p.a.), reported by Markit.
IO	% of share outstanding held by institutional investors for each firm-quarter, obtained from Thompson's 13-f files in WRDS.
$RET6M$	Cumulative return in the previous six months skipping the most recent month.
RET	Daily stock return reported by CRSP.
$ABRET$	Daniel et al.'s (1997) characteristic-adjusted abnormal returns using size, book-to-market, and momentum.
$ILLIQ$	Amihud (2002) daily price impact measure computed as the daily absolute returns divided by the dollar trading volume, all data obtained from CRSP.
$SPREAD$	Bid-ask spread based on Corwin and Schultz's (2012) method.
B/P	Compustat's CEQQ divided by MCAP, computed quarterly.
MKT	Daily excess (to risk free rate) market return, obtained from WRDS.
SMB	Daily factor portfolio return to the size factor, obtained from WRDS.
HML	Daily factor portfolio return to the value factor, obtained from WRDS.
MOM	Daily factor portfolio return to the momentum factor (UMD), obtained from WRDS.
$SPREAD$	Daily factor portfolio return to the bid-ask spread factor, based on Corwin and Schultz (2012). Stocks are sorted according to their average bid-ask spread in the previous month.
$D_{Ret(MKT)<-2.5\sigma}$	Indicator variable equal to 1 for trading days where the aggregate market return is more than 2.5 standard deviations below its average value in the previous day and 0 otherwise. This is computed using a GARCH(1,1) model on a rolling 252 trading-day basis.
D_{QUANT}	Indicator variable equal to 1 for trading days between Aug. 6, 2007, and Aug. 8, 2007, and 0 otherwise.
D_{LEHMAN}	Indicator variable equal to 1 for trading days between Sep. 16, 2008, and Sep.22, 2008, and 0 otherwise.
VIX	Implied volatility for S&P 500 options computed by the Chicago Board Options Exchange, obtained from Datastream (DSCODE: CBOEVIX).
TED	Difference between three-month Treasury and Eurodollar futures middle rate, obtained from Datastream (DSCODE: TRTEDSP).
$HAIRCUT$	Convertible bond spread relative to its "fair price" from Mitchell and Pulvino (2012).
$NOISE$	Funding illiquidity measure used by Hu et al. (2013) based on Treasury bond prices.
$CDS5y$	Five-day average of U.S. Banks Sector 5-year Credit Default Swap Index mid-rate Price, obtained from Datastream (DSCODE: USBANCD).

Figure 1: Hedge Fund Gross Leverage and Funding Liquidity

This figure plots daily hedge fund gross leverage ($HF\ Gross\ Leverage$) from Morgan Stanley for its fundamental long-short equity hedge fund clients of its prime brokerage arm and the first principal component of funding liquidity measures ($Funding\ Liquidity\ PC1$) from Jul. 2006 to Dec 2012. The sample includes U.S. long-short accounts with at least $50 million in equity and has been rebalanced every six to 12 months to keep it representative of historical accounts. Each fund is equally weighted in aggregate metric. We use the following funding liquidity proxies to extract the principal component. VIX is the daily implied volatility from S&P 500 index. TED is the daily Treasury-Eurodollar spread. $HAIRCUT$ is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). $NOISE$ is the illiquidity measure used by Hu et al. (2013). And $CDS5Y$ is the 5-year credit default swap index for the U.S. banking sector from Datastream.

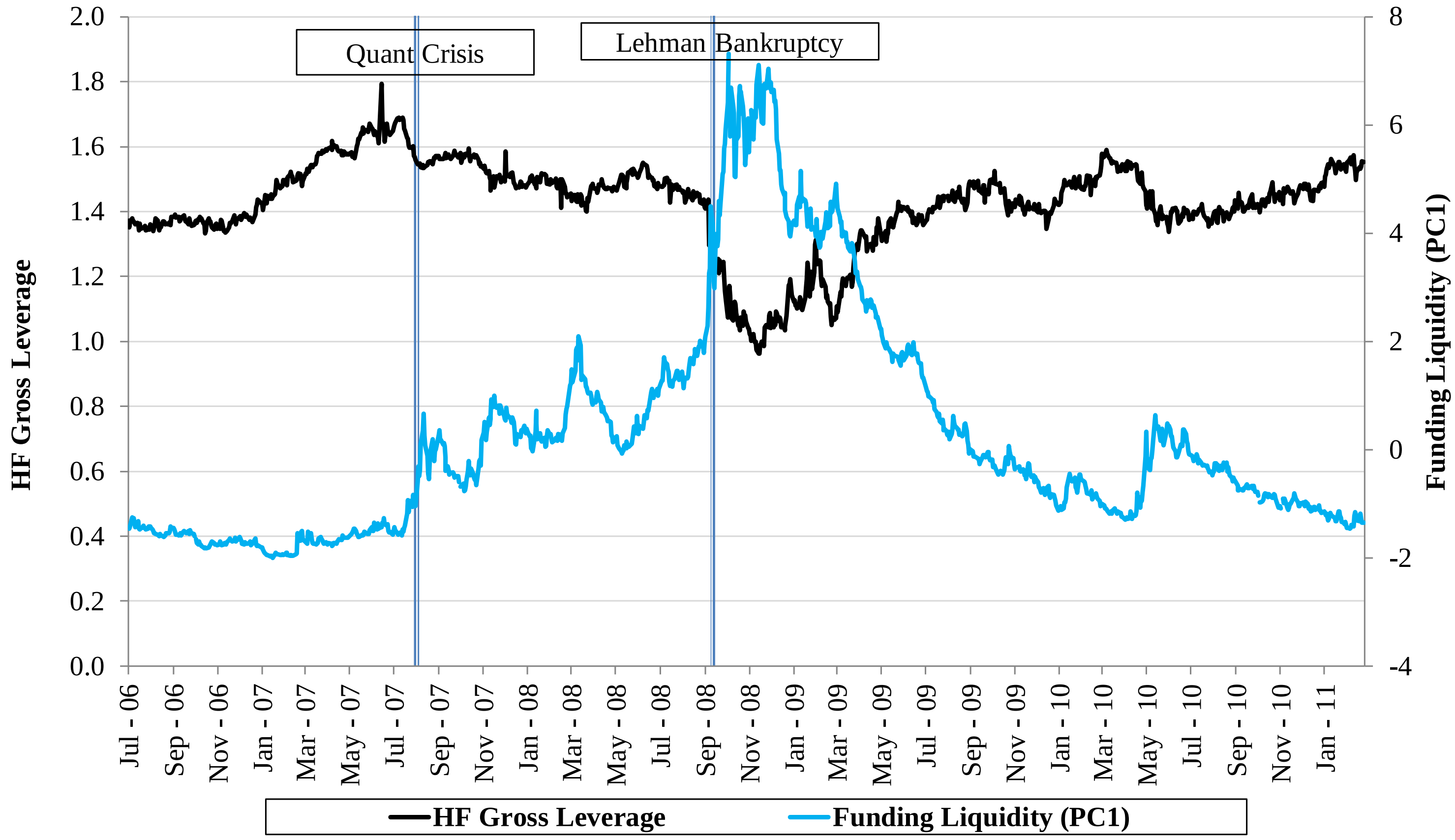


Figure 2: Aggregate $ONLOAN$

This figure plots daily $ONLOAN$ of U.S. firms from Jul. 2006 to May 2013 for various percentiles. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding.

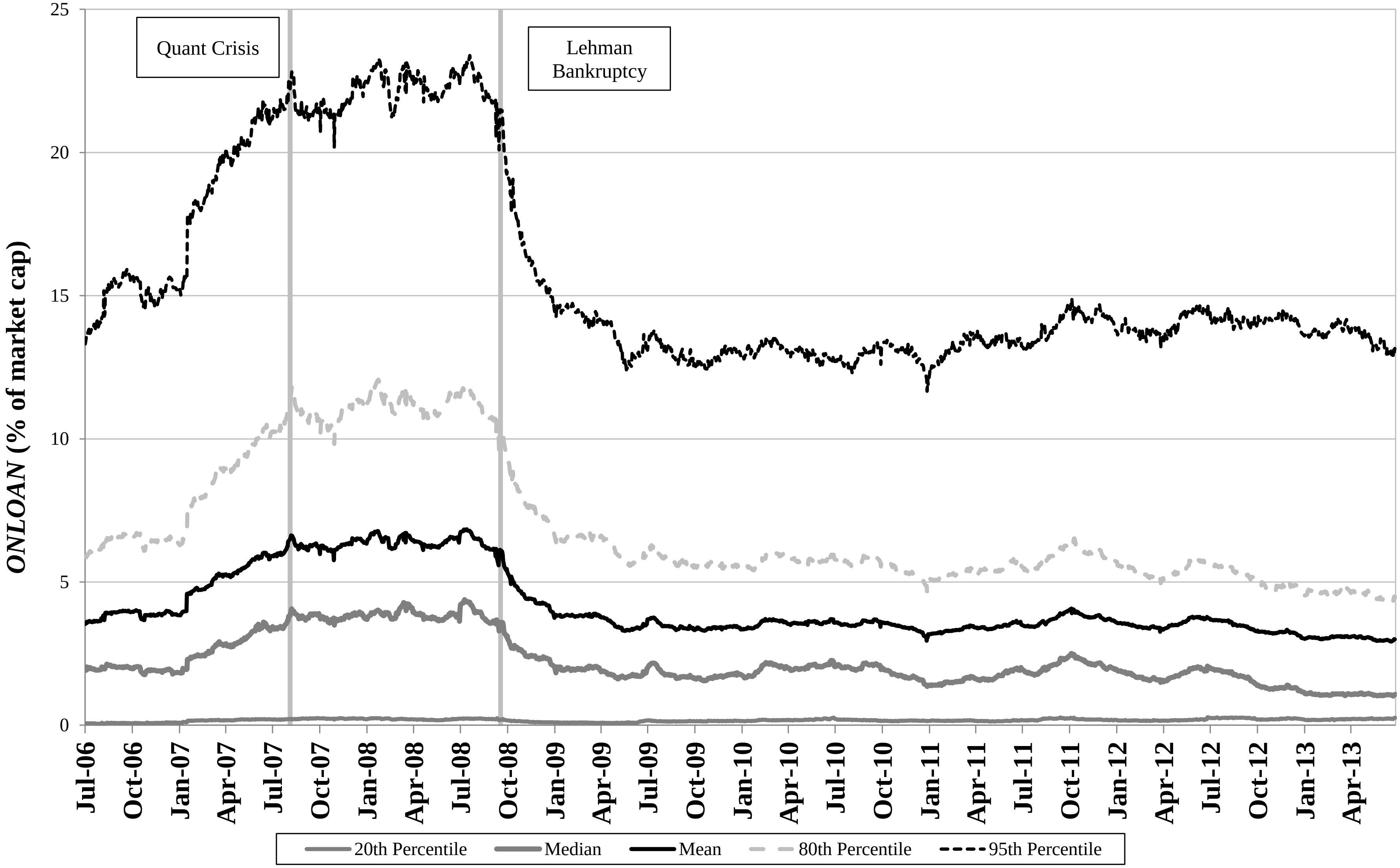


Figure 3: Daily Returns and Standard Deviations of Stock Portfolios sorted on $ONLOAN$

This figure plots the cumulative daily return of stock portfolios sorted on $ONLOAN$ from Jul. 2006 to May 2013. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding. We rank firms into quintiles and compute the equal- and value-weighted daily average returns of firms in each quintile. We plot cumulative returns of a portfolio that takes long (short) positions in securities in the LOW ($HIGH$) $ONLOAN$ quintile. The bottom panel displays daily standard deviations estimated from a GARCH(1,1) model.

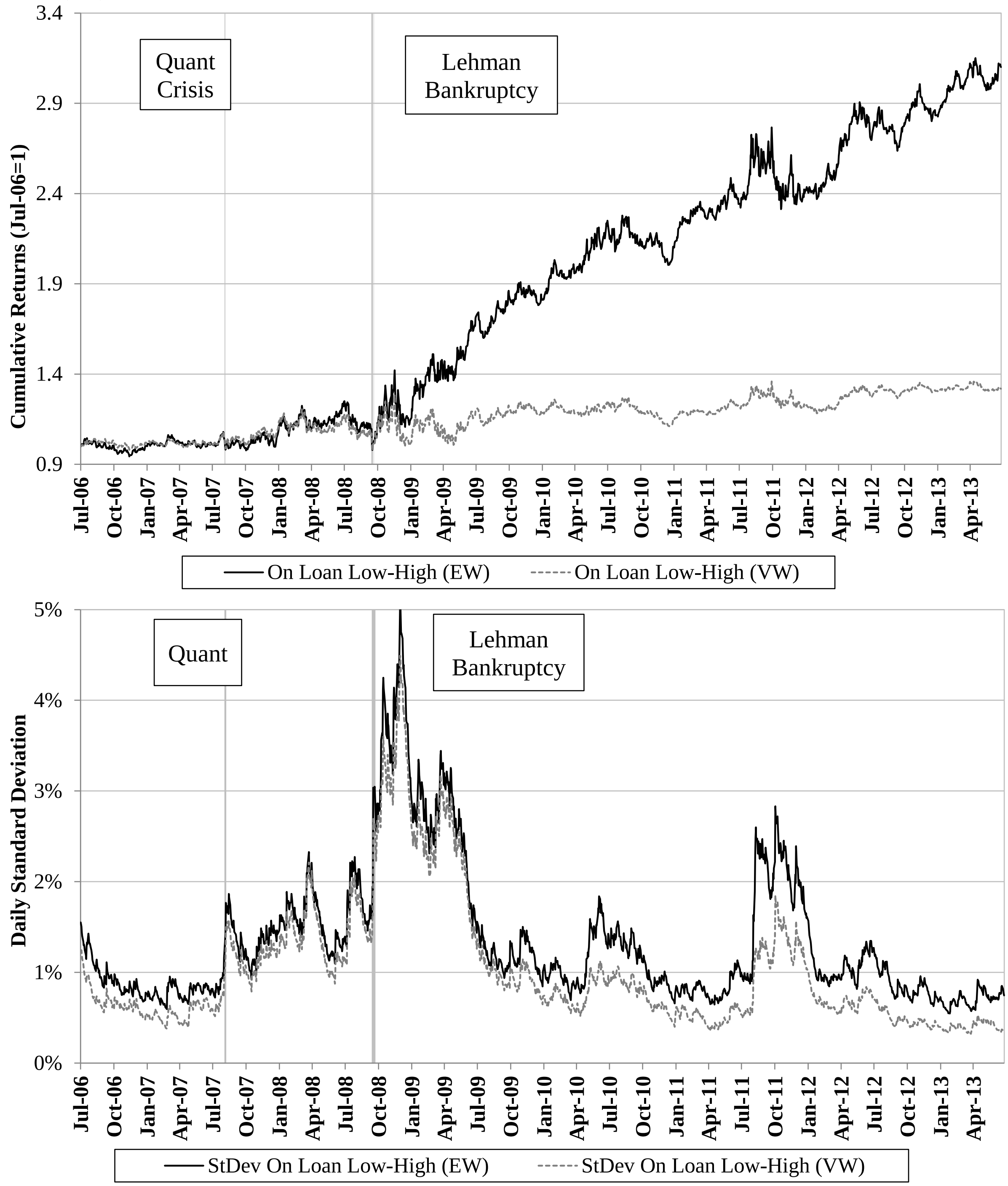


Figure 4: Extreme Return Days for High and Low Short $ONLOAN$ portfolios

This figure shows raw returns of stock portfolios sorted on $ONLOAN$ for days when the $LOW - HIGH$ portfolio return is 2.5 standard deviations below the mean. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding. Standardized returns are computed by dividing daily portfolio returns by standard deviations estimated from a GARCH(1,1) model for the period between Jul. 2006 and May 2013. We show returns for the bottom (LOW) and top ($HIGH$) quintiles of firms ranked by $ONLOAN$ and also for the $LOW - HIGH$ difference. The left panel displays data for equal-weighted portfolios and the right panel for value-weighted portfolios.

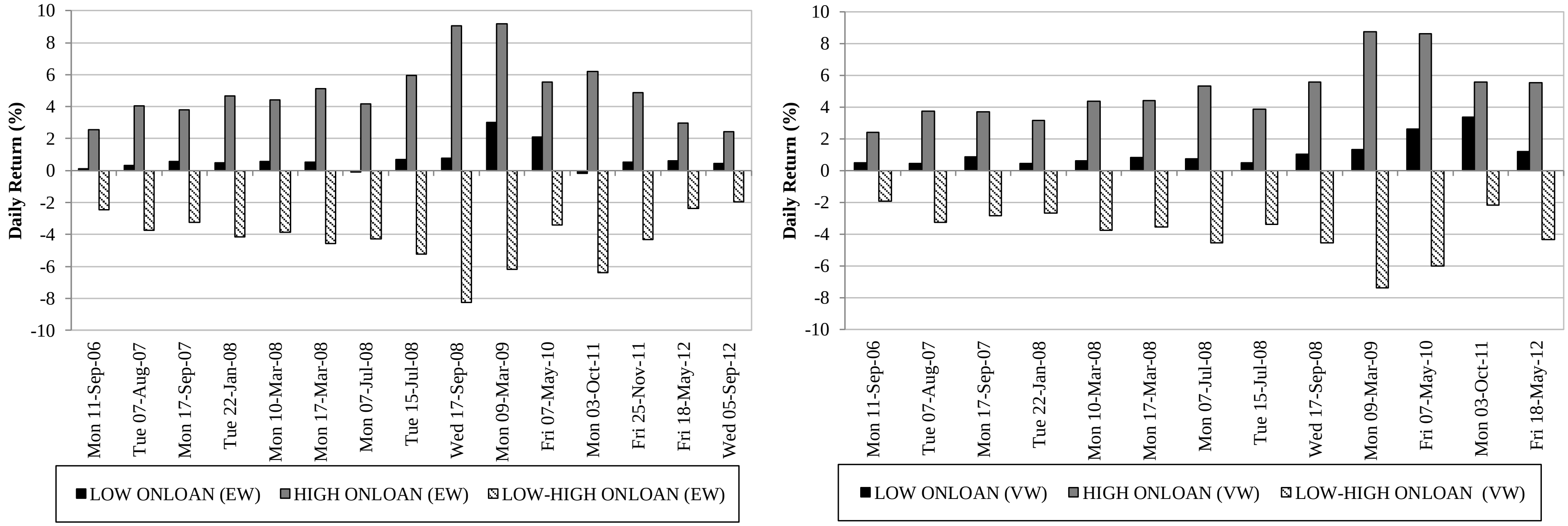
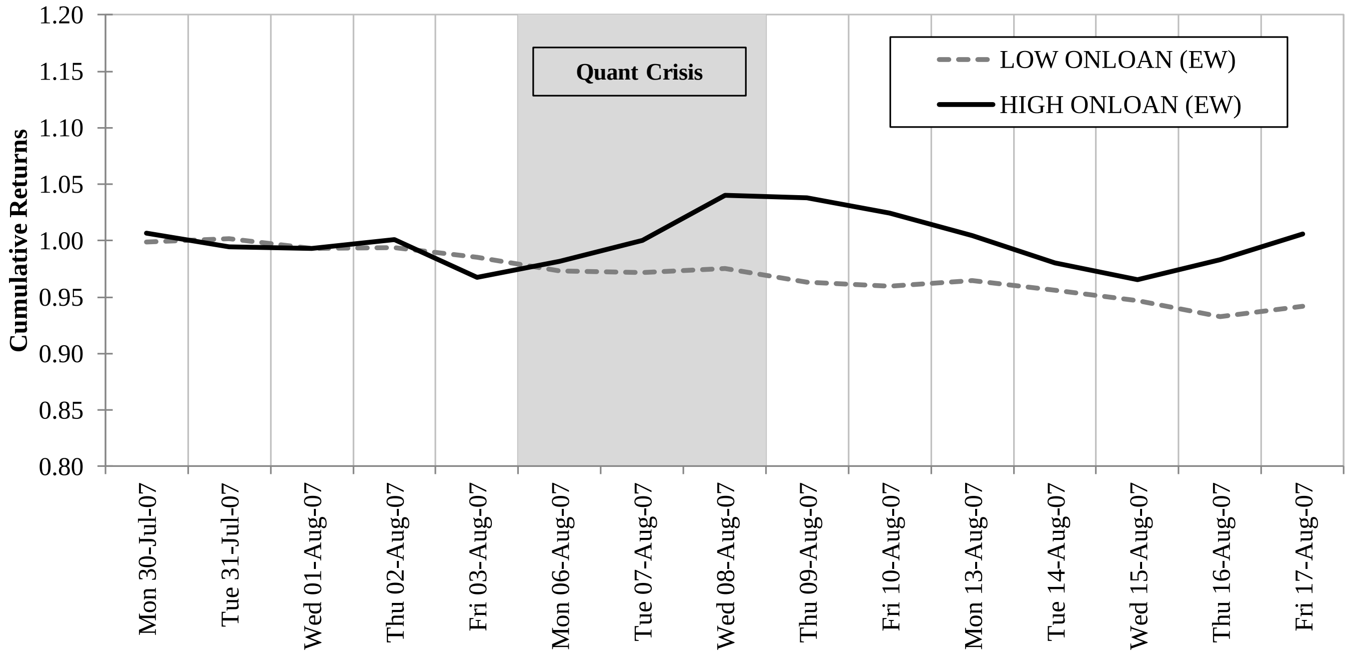


Figure 5: Abnormal Returns during the Quant Crisis and Lehman Brothers' Bankruptcy

The figure show the cumulative abnormal portfolio returns of high and low $ONLOAN$ portfolios around the Quant crisis and the Lehman Brothers bankruptcy. $ONLOAN$ is defined as the number of shares on loan divided by the total number of shares outstanding. Each day stocks are sorted into quintiles, and we compute the mean equal-weighted daily returns in each quintile. Abnormal returns are based on DGTW's characteristics-adjusted returns. The top figure displays returns around the Quant crisis in Aug. 2007, with the shaded area denoting the crisis period from Aug. 6 to Aug. 8, 2007. The lower figure shows abnormal returns around Lehman Brothers' bankruptcy in Oct. 2008, with the shaded area denoting the crisis period from Sep. 16 to 18, 2008.



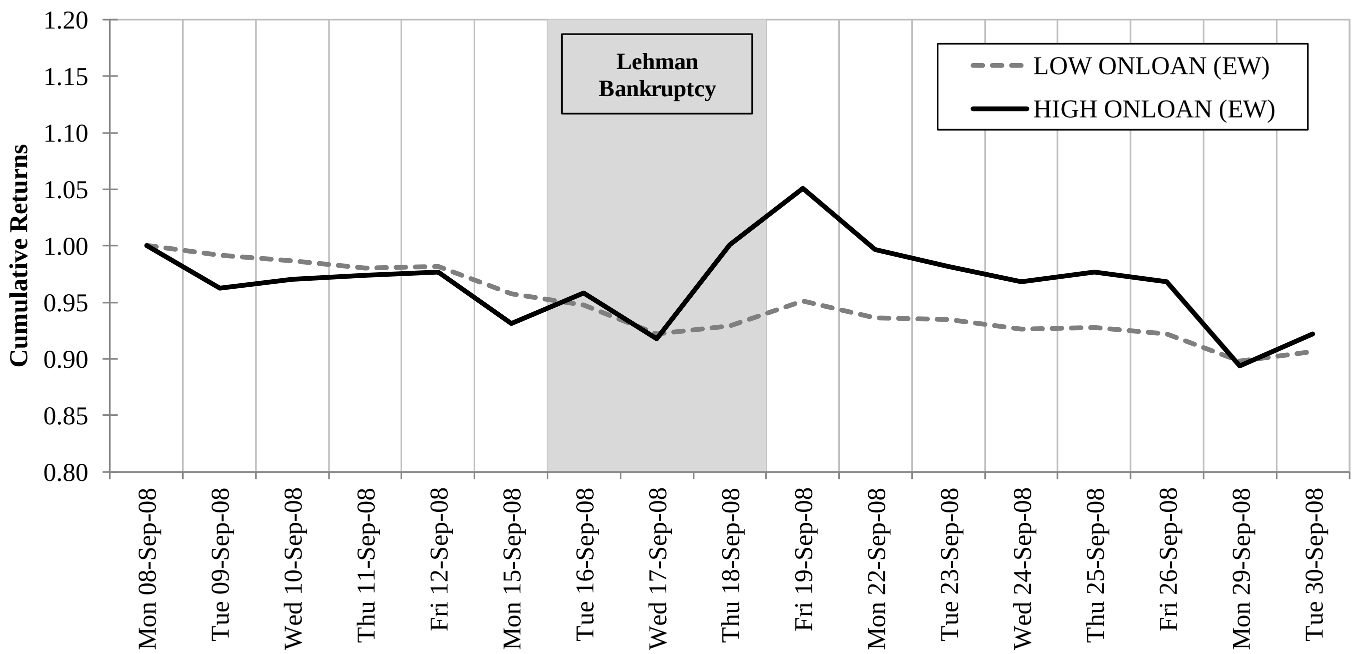


Table 1: Principal Component Analysis

The table shows results of principal component analysis used to extract the common factor of the five funding liquidity variables used in the paper. VIX is the daily implied volatility from S&P 500 index, TED is the daily Treasury-Eurodollar spread. $HAIRCUT$ is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). $NOISE$ is the illiquidity measure used by Hu et al. (2013). And $CDS5Y$ is the 5-year credit default swap index for the U.S. banking sector from Datastream. Panel A shows the estimated eigenvalues for each of the five estimated components, the fraction of the total variance explained by each one, and the cumulative variance. Panel B shows the factor loading for each of the five funding liquidity variables. Panel C displays the correlations of the estimated first principal component ($PC1$) and the funding liquidity variables.

Panel A: Eigenvalues and the Proportion of Variance Explained by Principal Components (N=1,611 days)

Principal Component (PC)	Eigenvalue	% Variance Explained	Cumulative % Variance
1	3.403	68%	68%
2	0.751	15%	83%
3	0.528	11%	94%
4	0.205	4%	98%
5	0.114	2%	100%

Panel B: Factor Loadings of First Principal Component (PC1)

	VIX	TED	$HAIRCUT$	$NOISE$	$CDS5y$
Loading	0.50	0.38	0.34	0.49	0.50

Panel C: Correlation between $PC1$ and Funding Liquidity Measures

Corr(↓,→)	$PC1$	VIX	TED	$HAIRCUT$	$NOISE$	$CDS5y$
$PC1$	1					
VIX	0.92	1				
TED	0.70	0.56	1			
$HAIRCUT$	0.63	0.53	0.27	1		
$NOISE$	0.90	0.79	0.48	0.48	1	
$CDS5y$	0.93	0.82	0.62	0.43	0.87	1

Table 2: Descriptive Statistics

This table summarizes the characteristics of stocks over the period between Jul. 2006 and May 2013 for 6,312,056 firm-day observations. $Size$ is market capitalization measured in millions of dollars. IO is total institutional share ownership. $SUPPLY$ is the total number of shares available to borrow divided by shares outstanding. $ONLOAN$ is the daily total number of shares on loan divided by shares outstanding. $SHORT\ INTEREST$ is the number of shorted shares reported in Compustat divided by shares outstanding. $SHORT\ VOLUME$ is the daily number of shares marked as short sales on NYSE divided by total volume. $UTILIZATION$ is the number of shares on loan divided by the total number of shares available to be lent. $VW\ Fee$ is the daily loan-weighted average annualized fee in basis points per annum. $SPREAD$ is the bid-ask spread estimated from Corwin and Schultz (2012). B/P is the book-to-market ratio. $RET6M$ is the cumulative return in the previous six-months, skipping the most recent month. VIX is the VIX volatility index. $Ret(MKT) < -2.5\sigma$ is an indicator variable equal to 1 if the market return is 2.5 standard deviations (taken from a GARCH(1,1) model) below the average. TED is the change in the Treasury-Eurodollar spread. $HAIRCUT$ is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). $NOISE$ is the illiquidity measure used by Hu et al. (2013). And $CDS5Y$ is the 5-year credit default swap index for the U.S. banking sector from Datastream. $\Delta(.)$ denotes changes between day t−2 and day t−1.

Variable	Mean	Median	Std. Dev.	Min	Max	Skew	Kurt
$Size$	4,191	510	18,300	0.26	658,000	0.00	0.00
IO	56%	62%	31%	0%	100%	-0.29	1.78
$SUPPLY$	18.87%	19.51%	12.32%	0.00%	100%	0.18	2.22
$ONLOAN$	4.18%	2.01%	5.51%	0.00%	27%	2.01	7.10
$SHORT\_INTEREST$	21.91%	4.37%	36.68%	0.00%	100%	1.61	3.69
$SHORT\_VOLUME$	20.96%	21.11%	7.98%	0.00%	100%	0.11	4.42
$UTILIZATION$	18.16%	9.67%	21.30%	0.00%	88.73%	1.53	4.66
$VW\ Fee\ (bps\ p.a.)$	101.37	12.31	319.06	-7.13	2,275	5.05	30.66
$SPREAD$	1.30%	0.98%	1.22%	0.00%	67.30%	6.42	123.55
B/P	0.73	0.57	0.63	-0.01	3.81	2.36	10.43
$RET6M$	3.47%	1.15%	38.00%	-77.06%	158.33%	1.05	5.98
$Ret(MKT) < -2.5\sigma$	0.019	0.000	0.136	0.000	1.000	7.07	50.98
VIX	23.07	20.47	10.97	9.89	81.00	1.93	7.68
TED	0.63%	0.39%	0.62%	0.09%	4.58%	2.36	10.39
$HAIRCUT$	2.07%	1.13%	3.01%	-1.31%	13.69%	1.83	5.69
$NOISE$	3.99%	2.74%	3.81%	0.72%	20.47%	2.30	8.15
$CDS5y$	131.14	122.58	80.8	10.2	595.99	0.76	4.70
ΔVIX	0.000	0.000	0.020	-0.170	0.170	0.52	17.87
ΔTED	0.00%	0.00%	0.08%	-0.80%	1.00%	0.66	48.18
$\Delta HAIRCUT$	0.00%	0.00%	0.27%	-3.99%	2.25%	-1.46	46.00
$\Delta NOISE$	0.00%	0.00%	0.30%	-2.06%	1.92%	-0.03	10.74
$\Delta CDS5y$	0.01	0.02	2.51	-15.92	16.69	0.25	11.69
$\Delta PC1$	0.00%	-0.01%	0.14%	-1.17%	1.15%	0.79	16.43

Table 3: Equal-Weighted Stock Portfolio Returns sorted on $ONLOAN$

The table displays regressions of stock portfolios sorted by $ONLOAN$, with daily U.S. stock returns between Jul. 2006 and May 2013. We form portfolios by ranking stocks into quintiles based on $ONLOAN$ in the previous day and computing equal-weighted daily returns of selling High $ONLOAN$ stocks and buying Low $ONLOAN$ stocks. $ONLOAN$ is the total amount on loan divided by market capitalization. MKT is excess market return above the risk-free rate. SMB is the return on a portfolio of small stocks minus the return on a portfolio of big stocks. HML is the return on a portfolio of high book-to-market (value) minus low book-to-market (growth) stocks. MOM is the return on a portfolio of prior winners minus the return on a portfolio of prior losers. And $SPREAD$ is the return on a portfolio of high-spread minus low-spread stocks. $D_{\mathrm{Ret(MKT)}<2.5\sigma}$ is an indicator variable equal to 1 if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sep. 16 and Sep. 18, 2008, and 0 otherwise. ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day. $\Delta HAIRCUT$ is the convertible bond spread relative to its fair price from Mitchell and Pulvino (2012). $\Delta NOISE$ is the illiquidity measure used by Hu et al. (2013), $\Delta CDS5y$ the change in Datastream's U.S. Banking Sector credit default swap index, and $\Delta PC1$ is the principal component from the funding liquidity variables above. Returns and risk factors MKT, SMB, HML, MOM and $SPREAD$ are measured at period t, while other explanatory variables are measured at period t−1. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

Coeff.	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Intercept$	+	0.094***	0.106***	0.096***	0.093***	0.093***	0.091***	0.096***	0.105***
		[0.013]	[0.013]	[0.013]	[0.013]	[0.013]	[0.014]	[0.013]	[0.014]
β_{MKT}	-	-0.816***	-0.830***	-0.801***	-0.815***	-0.811***	-0.811***	-0.813***	-0.808***
		[0.021]	[0.021]	[0.021]	[0.021]	[0.021]	[0.022]	[0.020]	[0.023]
β_{SMB}	-	-0.786***	-0.779***	-0.786***	-0.786***	-0.795***	-0.807***	-0.781***	-0.805***
		[0.045]	[0.045]	[0.044]	[0.045]	[0.046]	[0.046]	[0.045]	[0.047]
β_{HML}	-	-0.052	-0.058	-0.046	-0.043	-0.065	-0.059	-0.052	-0.069
		[0.050]	[0.048]	[0.049]	[0.050]	[0.050]	[0.050]	[0.050]	[0.050]
β_{MOM}	+	0.216***	0.208***	0.222***	0.215***	0.219***	0.215***	0.215***	0.215***
		[0.025]	[0.024]	[0.024]	[0.025]	[0.024]	[0.025]	[0.024]	[0.024]
β_{SPREAD}	+	0.042**	0.048***	0.034*	0.044**	0.045**	0.046**	0.039**	0.046**
		[0.019]	[0.018]	[0.020]	[0.019]	[0.019]	[0.020]	[0.019]	[0.020]
$\beta_{Ret(MKT)<-2.5\sigma}$	-		-0.354***						-0.320***
			[0.124]						[0.118]
β_{QUANT}	-		-1.579***						-1.601***
			[0.063]						[0.092]
β_{LEHMAN}	-		-2.511***						-1.885***
			[0.275]						[0.178]
$\beta_{\Delta VIX}$	-			-4.851***					
				[0.921]					
$\beta_{\Delta TED}$	-				-1.267***				
					[0.360]				
$\beta_{\Delta HAIRCUT}$	-					-0.208**			
						[0.092]			
$\beta_{\Delta NOISE}$	-						-0.246***		
							[0.075]		
$\beta_{\Delta CDS5y}$	-							-1.294**	
								[0.656]	
$\beta_{\Delta PC1}$	-								-0.955***
									[0.153]
# Days		1,756	1,756	1,755	1,755	1,747	1,606	1,751	1,594
Adj. R2		0.868	0.876	0.873	0.872	0.869	0.869	0.870	0.881

Table 4: Equal-Weighted Stock Portfolio Returns sorted on Additional Proxies for Short-Selling Intensity

The table shows regressions of equal-weighted stock portfolio returns sorted on different proxies of short-selling intensity, $ONLOAN$, $UTILIZATION$ and $SHORT\_VOLUME$, using daily U.S. stock returns between Jul. 2006 and May 2013. We rank stocks into quintiles based on values of short-selling proxies in the previous day and compute returns of the portfolio that sells high short-selling intensity stocks and buys low short-selling intensity stocks. $ONLOAN$ is the total amount on loan divided by market capitalization; $UTILIZATION$, defined as the number of shares on loan divided by the number of shares available to borrow; and $SHORT\_VOLUME$, the number of shares traded short divided by the total number of traded shares on the NYSE SuperDOT system. $SHORT\_VOLUME$ is only available for the Jul. 2006 to Jun. 2012 period. Returns and risk factors MKT, SMB, HML, MOM and $SPREAD$ are measured at period t, while other explanatory variables are measured at period $t-1$. Explanatory variables are the same as in Table 3. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

Short-Selling Intensity Variable		$ONLOAN$		$UTILIZATION$		$SHORT\_VOLUME$	
Coeff.	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	+	0.106***	0.105***	0.106***	0.107***	0.069***	0.066***
		[0.014]	[0.014]	[0.012]	[0.012]	[0.015]	[0.016]
β_{MKT}	-	-0.807***	-0.808***	-0.612***	-0.612***	-0.098***	-0.103***
		[0.022]	[0.023]	[0.020]	[0.020]	[0.021]	[0.022]
β_{SMB}	-	-0.801***	-0.805***	-0.703***	-0.702***	-0.188***	-0.201***
		[0.047]	[0.047]	[0.045]	[0.045]	[0.048]	[0.051]
β_{HML}	-	-0.068	-0.069	-0.059	-0.059	0.023	0.035
		[0.049]	[0.050]	[0.043]	[0.045]	[0.045]	[0.048]
β_{MOM}	+	0.216***	0.215***	0.213***	0.213***	0.097***	0.096***
		[0.024]	[0.024]	[0.021]	[0.021]	[0.027]	[0.028]
β_{SPREAD}	+	0.046**	0.046**	-0.014	-0.015	0.067***	0.071***
		[0.019]	[0.020]	[0.016]	[0.016]	[0.016]	[0.016]
$\beta_{Ret(MKT)<-2.5\sigma}$	-	-0.285**	-0.320***	-0.152	-0.168	0.005	-0.062
		[0.116]	[0.118]	[0.119]	[0.119]	[0.149]	[0.155]
β_{QUANT}	-	-1.588***	-1.601***	-2.130***	-2.134***	-2.250***	-2.270***
		[0.087]	[0.092]	[0.348]	[0.353]	[0.628]	[0.639]
β_{LEHMAN}	-	-2.135***	-1.885***	-2.297***	-2.256***	-1.629***	-1.126***
		[0.367]	[0.178]	[0.525]	[0.468]	[0.270]	[0.252]
$\beta_{\Delta VIX}$	-	-3.897***		-2.923***		-1.898	
		[0.886]		[0.888]		[1.182]	
$\beta_{\Delta TED}$	-	-0.455		-0.520*		-0.188	
		[0.364]		[0.312]		[0.402]	
$\beta_{\Delta HAIRCUT}$	-	-0.166		-0.166*		-0.166*	
		[0.103]		[0.091]		[0.098]	
$\beta_{\Delta NOISE}$	-	-0.136**		-0.150**		0.193**	
		[0.066]		[0.061]		[0.097]	
$\beta_{\Delta CDS5y}$	-	-1.236*		-0.698		-1.703***	
		[0.704]		[0.533]		[0.452]	
$\beta_{\Delta PC1}$	-		-0.955***		-0.808***		-0.395**
			[0.153]		[0.149]		[0.190]
# Days		1,594	1,594	1,594	1,594	1,467	1,467
Adj. R2		0.882	0.881	0.874	0.874	0.198	0.167

Table 5: Value-Weighted and Return-Weighted Stock Portfolio Returns sorted on Proxies for Short-Selling Intensity

The table shows regressions of value-weighted (VW) and return-weighted (RW) stock portfolio returns sorted on alternative proxies of short-selling intensity, $ONLOAN$, $UTILIZATION$ and $SHORT\_VOLUME$, using daily U.S. stock returns between Jul. 2006 and May 2013. We rank stocks into quintiles based on values of short-selling proxies in the previous day and compute returns of the portfolio that sells high short-selling intensity stocks and buys low short-selling intensity stocks. Value-weighted portfolios are constructed using a stock's market capitalization in the previous day to form weights, while return-weighted (RW) portfolios use a stock's gross return in the previous day as in Asparouhova et al. (2013). $ONLOAN$ is the total amount on loan divided by market capitalization; $UTILIZATION$, defined as the number of shares on loan divided by the number of shares available to borrow; and $SHORT\_VOLUME$, the number of shares traded short divided by the total number of traded shares on the NYSE SuperDOT system. $SHORT\_VOLUME$ is only available for the Jul. 2006 to Jun. 2012 period. Returns and risk factors MKT, SMB, HML, MOM and $SPREAD$ are measured at period t, while other explanatory variables are measured at period $t{-}1$. Explanatory variables are described in Table 3. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level.

Short-Selling Intensity Variable		$ONLOAN$		$UTILIZATION$		$SHORT\_VOLUME$	
Portfolio Weighting		VW	RW	VW	RW	VW	RW
Coeff.	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	+	0.056***	0.055***	0.063***	0.065***	0.074***	0.073***
		[0.013]	[0.015]	[0.011]	[0.014]	[0.015]	[0.015]
β_{MKT}	-	-0.582***	-0.793***	-0.261***	-0.677***	-0.085***	-0.099***
		[0.024]	[0.025]	[0.019]	[0.024]	[0.025]	[0.023]
β_{SMB}	-	-0.567***	-0.630***	-0.728***	-0.611***	-0.259***	-0.195***
		[0.046]	[0.052]	[0.043]	[0.055]	[0.058]	[0.049]
β_{HML}	-	-0.020	-0.053	-0.167***	-0.093*	0.002	0.032
		[0.047]	[0.057]	[0.045]	[0.054]	[0.048]	[0.046]
β_{MOM}	+	0.247***	0.179***	0.279***	0.192***	0.154***	0.083***
		[0.022]	[0.026]	[0.019]	[0.025]	[0.024]	[0.025]
β_{SPREAD}	+	0.001	0.047**	-0.033*	0.013	0.019	0.043***
		[0.016]	[0.019]	[0.019]	[0.018]	[0.013]	[0.014]
$\beta_{Ret(MKT)<-2.5\sigma}$	-	-0.210	-0.268**	-0.018	-0.204	-0.047	-0.029
		[0.134]	[0.122]	[0.111]	[0.129]	[0.162]	[0.130]
β_{QUANT}	-	-1.414***	-1.590***	-2.019***	-2.221***	-1.754***	-2.268***
		[0.143]	[0.080]	[0.445]	[0.295]	[0.418]	[0.559]
β_{LEHMAN}	-	-1.553***	-2.011***	-2.269***	-2.646***	-1.010***	-1.066***
		[0.209]	[0.182]	[0.626]	[0.485]	[0.335]	[0.273]
$\beta_{\Delta PC1}$	-	-0.818***	-0.993***	-0.220	-0.934***	-0.182	-0.403**
		[0.153]	[0.165]	[0.146]	[0.170]	[0.216]	[0.183]
# Days		1,594	1,594	1,594	1,594	1,467	1,467
Adj. R2		0.839	0.852	0.831	0.847	0.256	0.170

Table 6: Equal-Weighted Stock Portfolios sorted on $SHORT\_INTEREST$ (1990–2013)

The table displays regressions of stock portfolios sorted on $SHORT\_INTEREST$, with daily U.S. stock returns between Jan. 1990 and Aug. 2013. We form portfolios by ranking stocks into quintiles based on $SHORT\_INTEREST$ at the end of the previous month and carrying these ranks forward daily until the beginning of the next month. Our dependent variable is the equal-weighted daily return of selling high $SHORT\_INTEREST$ stocks and buying low $SHORT\_INTEREST$ stocks. $SHORT\_INTEREST$ is the number of shares sold short divided by the total number of outstanding shares. Returns and risk factors MKT, SMB, HML, MOM and $SPREAD$ are measured at period *t*, while other explanatory variables are measured at period $t-1$. Explanatory variables are the same as in Table 3 and defined in the appendix. We report White-adjusted standard deviations in brackets and significance levels are indicated as follows: ***(**)=statistical significance at the 1% (5%) level.

Coeff.	Predicted Sign	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Intercept$	+	0.038***	0.043***	0.038***	0.037***	0.079***	0.034***	0.078***
		[0.008]	[0.008]	[0.008]	[0.008]	[0.011]	[0.008]	[0.010]
β_{MKT}	-	-0.738***	-0.747***	-0.736***	-0.737***	-0.797***	-0.737***	-0.802***
		[0.010]	[0.010]	[0.010]	[0.010]	[0.017]	[0.010]	[0.016]
β_{SMB}	-	-0.515***	-0.514***	-0.516***	-0.515***	-0.829***	-0.521***	-0.813***
		[0.023]	[0.023]	[0.023]	[0.023]	[0.036]	[0.023]	[0.033]
β_{HML}	-	-0.277***	-0.278***	-0.276***	-0.275***	0.002	-0.282***	0.007
		[0.019]	[0.018]	[0.018]	[0.018]	[0.039]	[0.019]	[0.035]
β_{MOM}	+	0.100***	0.094***	0.100***	0.099***	0.170***	0.102***	0.159***
		[0.013]	[0.013]	[0.013]	[0.013]	[0.021]	[0.013]	[0.019]
β_{SPREAD}	+	0.062***	0.064***	0.061***	0.063***	0.050***	0.067***	0.045***
		[0.009]	[0.009]	[0.009]	[0.009]	[0.018]	[0.008]	[0.016]
$\beta_{Ret(MKT)<-2.5\sigma}$	-		-0.303***					
			[0.080]					
β_{QUANT}	-		-1.610***					
			[0.311]					
β_{LEHMAN}	-		-2.160***					
			[0.208]					
$\beta_{\Delta VIX}$	-			-2.185***				
				[0.647]				
$\beta_{\Delta TED}$	-				-0.558***			
					[0.174]			
$\beta_{\Delta HAIRCUT}$	-					-0.159**		
						[0.074]		
$\beta_{\Delta NOISE}$	-						-0.038	
							[0.026]	
$\beta_{\Delta CDS5y}$	-							-1.206**
								[0.593]
# Days		5,964	5,964	5,963	5,963	1,965	5,689	2,427
Adj. R2		0.756	0.761	0.757	0.757	0.877	0.753	0.879

Table 7: Cumulative Returns of Equal-Weighted Stock Portfolios sorted on $ONLOAN$

The table displays regressions of stock portfolio returns sorted by $ONLOAN$, using daily U.S. stock returns between Jul. 2006 and May 2013 based on equation (2) in the text. The dependent variable $RET_{i,t+j}$ is the cumulative returns from t to $t+j$ after portfolio formation. We form portfolios by ranking stocks into quintiles based on $ONLOAN$ in the previous day and computing equal-weighted daily returns of selling high $ONLOAN$ stocks and buying low $ONLOAN$ stocks. $ONLOAN$ is the total amount on loan divided by market capitalization. MKT is the excess market return above the risk-free rate. SMB is the return on a portfolio of small stocks minus the return on a portfolio of big stocks. HML is the return on a portfolio of high book-to market (value) minus low book-to-market (growth) stocks. MOM is the return on a portfolio of prior winners minus the return on a portfolio of prior losers. And $SPREAD$ is the return on a portfolio of high-spread minus low-spread stocks. $D_{Ret(MKT)<2.5\sigma}$ is an indicator variable equal to 1 if the standardized market return in the previous day is 2.5 standard deviations below (above) the mean. D_{QUANT} is an indicator variable equal to 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sep. 16 and Sep. 18, 2008, and 0 otherwise. ΔVIX is the daily change in the VIX volatility index. ΔTED is the daily change in the Treasury-Eurodollar spread in the previous day. $\Delta HAIRCUT$ is the daily change in the spread of convertible bonds relative to their fair price from Mitchell and Pulvino (2012). $\Delta NOISE$ is the illiquidity measure used by Hu et al. (2013), $\Delta CDS5Y$ is the change in five year credit default swap prices for the U.S. banking sector, and $\Delta PC1$ is the change in the first principal component of funding liquidity variables estimated in Table 3. Returns and risk factors MKT, SMB, HML, MOM and $SPREAD$ are measured at period t, while other explanatory variables are measured at period t−1. We report HAC standard errors in brackets using the optimum lag-selection algorithm proposed by Newey and West (1994). Significance levels are indicated as follows: ***(**)=significant at the 1% (5%) level

$t+j$	$D_{Ret(MKT)<-2.5\sigma}$	D_{QUANT}	D_{LEHMAN}	ΔVIX	ΔTED	$\Delta HAIRCUT$	$\Delta NOISE$	$\Delta CDS5y$	$\Delta PC1$
	(1a)	(1b)	(1c)	(2)	(3)	(4)	(5)	(6)	(7)
1	-0.354***	-1.579***	-2.511***	-4.851***	-1.267***	-0.208***	-0.246***	-1.294**	-0.955***
2	-0.501***	-3.079***	-4.544***	-8.436***	-1.751**	-0.247*	-0.275**	-2.638*	-1.479***
3	-0.706***	-4.056***	-6.041***	-10.110***	-2.232***	-0.453**	-0.374**	-3.687**	-1.870***
4	-0.681**	-3.974***	-6.510***	-12.239***	-3.065***	-0.564**	-0.322*	-4.848**	-2.307***
5	-0.783**	-3.102***	-6.956***	-14.375***	-3.501***	-0.568*	-0.531**	-5.215**	-2.735***
20	-3.050***	-0.651	-5.281*	-17.012***	-4.178**	-1.423***	-0.691**	-16.617***	-4.530***
60	-3.647***	-2.729	-7.128**	-24.778***	-4.625***	-1.321***	-0.207	-17.904**	-5.602***
80	1.021	-1.803*	-6.409**	4.641	-3.768	0.123	0.817	-3.861	0.647

Table 8: Panel Regressions of Changes in $ONLOAN$ of Individual Stocks as a Function of Funding Liquidity Proxies and Crisis Indicator Variables

The table displays selected coefficients of panel data regressions of changes in equity loan quantities between Jul. 2006 and May 2013, based on equation (3) in the text. The dependent variable is $\Delta ONLOAN_{\mathrm{i,t+3+j}}$, defined as the difference in $ONLOAN$ between day t+3+j and t+3, which captures short selling activity between *t+j* and *t+j-1*. Explanatory variables include $ONLOAN$, defined as the total amount on loan divided by market capitalization on day $t-1$; $HIGH\_ONLOAN$, an indicator variable to one if the stock is on the top quintile of $ONLOAN$, 0 otherwise; LOW_ONLOAN, an indicator variable equal to 1 if the stock belongs to the bottom quintile of $ONLOAN$, 0 otherwise; crisis-indicator variables; funding liquidity variables; and controls. We also interact all control variables, $ONLOAN, HIGH\_ONLOAN$, and LOW_ONLOAN with the crisis-indicator variables and funding liquidity variables. The control variables are $BETA$, $SIZE$, B/P, $RET6M$, $RETURN_{t-1}$, $SPREAD$, and $ILLIQ$. Each column reports coefficients of interactions of $ONLOAN$ with crisis indicators or funding liquidity variable. D_{QUANT} is an indicator variable equal to 1 in the period between Aug. 6 and Aug. 8, 2007, and 0 otherwise. D_{LEHMAN} is an indicator variable equal to 1 in the period between Sep. 16 and Sep. 18, 2008, and 0 otherwise. ΔVIX is the daily change in the VIX volatility index. ΔTED is the daily change in the treasury-Eurodollar spread in the previous day. $\Delta HAIRCUT$ is the daily change in the spread of convertible bonds relative to their fair price from Mitchell and Pulvino (2012). $\Delta NOISE$ is the illiquidity measure used by Hu et al. (2013), $\Delta CDS5Y$ is the change in 5-year credit default swap prices for the U.S. banking sector, and $\Delta PC1$ is the change in the first principal component of funding liquidity variables estimated in Table 1. All regressions include year-month fixed-effects, and we report robust standard errors clustered at the firm level in brackets. Significance levels are indicated as follows: *** (**)=statistical significance at the 1% (5%) level.

	Liquidity	Interactions of $High\ ONLOAN$ with *Liquidity Variable*							
	Variable	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*	*t+20*	*t+60*	*t+80*
(1a)	$D_{Ret(MKT)<-2.5\sigma}$	-0.004	-0.001	-0.037***	-0.040***	-0.022*	-0.176***	-0.266***	-0.223***
(1b)	D_{QUANT}	-0.144***	-0.309***	-0.527***	-0.693***	-0.760***	-0.792***	-0.382**	-0.306*
(1c)	D_{LEHMAN}	-0.193***	-0.371***	-0.535***	-0.698***	-0.841***	-1.874***	-3.476***	-3.900***
(2)	ΔVIX	-0.034	-0.136***	-0.191***	-0.252***	-0.416***	-0.984***	-1.761***	-1.737***
(3)	ΔTED	-0.034***	-0.050***	-0.067***	-0.083***	-0.098***	-0.282***	-0.618***	-0.738***
(4)	$\Delta HAIRCUT$	-0.020***	-0.032***	-0.046***	-0.046***	-0.050***	-0.102***	-0.180***	-0.196***
(5)	$\Delta NOISE$	-0.005	-0.010**	-0.020***	-0.008	0.005	0.013	0.017	-0.002
(6)	$\Delta CDS5y$	0.065***	0.086***	0.097***	0.129***	0.128***	0.194***	0.054**	-0.007
(7)	$\Delta PC1$	-0.021***	-0.034***	-0.053***	-0.068***	-0.117***	-0.281***	-0.578***	-0.616***